DOCTORAL THESIS

BEHAVIORAL MICROFOUNDATIONS OF RETAIL CREDIT MARKETS

A theoretical and experimental approximation

AUTHOR: DAVID PEÓN POSE

Co-director: Dr. Anxo Calvo Silvosa
Co-director: Dr. Manel Antelo Suárez

A Coruña, 2014

UNIVERSIDADE DA CORUÑA

DEPARTAMENTO DE ECONOMÍA FINANCEIRA E CONTABILIDADE

Programa de Doutoramento:
Competitividade, innovación e desenvolvemento: Análise económica e empresarial[1]

[1] Programa regulado polo RD 1393/2007

THESIS CO-DIRECTOR'S DECLARATION

I certify that the thesis of the PhD candidate David Peón Pose fulfills all the requirements to be awarded with a doctoral degree.

Certifico que a tese do doutorando David Peón Pose cumpre todos os requerimentos para optar ao grao de doutor.

Certifico que la tesis del doctorando David Peón Pose cumple todos los requisitos para optar al grado de doctor.

A Coruña, 25.09.2014

Dr. Anxo Calvo Silvosa
Associate Professor
Departamento de Economía Financeira e Contabilidade
Universidade da Coruña

THESIS CO-DIRECTOR'S DECLARATION

I certify that the thesis of the PhD candidate David Peón Pose fulfills all the requirements to be awarded with a doctoral degree.

Certifico que a tese do doutorando David Peón Pose cumpre todos os requerimentos para optar ao grao de doutor.

Certifico que la tesis del doctorando David Peón Pose cumple todos los requisitos para optar al grado de doctor.

Santiago de Compostela, 25.09.2014

Dr. Manel Antelo Suárez
Associate Professor
Departamento de Fundamentos de Análise Económica
Universidade de Santiago de Compostela

I’ve been a miner for a heart of gold

xopa, cando todo empezou non estabades aquí
cando rematou, non había no mundo nada máis importante

ACKNOWLEDGEMENTS / AGRADECEMENTOS

Tentar agradecer nunhas breves liñas a todas as persoas e institucións que, durante os máis de catro anos de desenvolvemento e elaboración desta tese doutoral, prestaron a súa colaboración desinteresada ou influíron nos meus pensamentos e coñecementos sintetizados na mesma, sería de todo inacadable. Vaia o meu recoñecemento e agradecemento por tanto a todos vós, profesores, persoal e alumnos da FEE pola vosa axuda, e en particular a todos os compañeiros do Departamento de Economía Financeira e Contabilidade.

Quixera agradecer persoalmente a aqueles que realizaron achegas de moita valía na elaboración dos artigos e publicacións que resultaron desta tese: os compañeiros Ángel Fernández, Cristina Anido, Emma Iglesias, Fernando de Llano, Flora Muíño, José A. Novo, José M. Seijas, Manuel Gómez, Marcos Vizcaíno, Paolo Rungo e Rafael Gómez, así como a Andrea Ceschi, Javier Iglesias, Juan Vilar, Jose A. Vilar, Manuel F. Grela, Tomasz Michalski, revisores anónimos e editores dos diversos journals. O meu agradecemento especial a Enrico Cervellati e Jorge Rodriguez pola súa orientación. Colaboraron moi especialmente na elaboración dalgunhas partes da tese os compañeiros Paulino Martínez no deseño da aplicación informática e Xosé M. Filgueira en axuda técnica. Por último, agracecer a todos e cada un dos 126 alumnos participantes no experimento a súa participación.

Expreso finalmente a miña gratitude a todos aqueles os que, sen a súa colaboración, esta tese nunca tería sido unha realidade. Ao Grupo BBVA por facilitarme a miña dedicación á tese durante catro anos. Ao Departamento de Economía Financeira e Contabilidade da UDC por todas as facilidades para o desempeño das miñas actividades docentes e de investigación. A miña enorme gratitude e recoñecemento aos meus directores de tese, Dr. Manel Antelo e Dr. Anxo Calvo, pola súa sabedoría, orientación, e apoio en todo momento. Tivestes moita paciencia...

E moi especialmente a meus pais e irmans, e a María, a quen lle debo todo o seu apoio estes anos, a paciencia e o ánimo nas interminables horas e preocupacións que deu de si este traballo, e por sacar adiante ás nosas xoias, Anxo e Pablo. Quérovos.

DECLARATION

"I certify that the contents of this document are entirely my own work and that any quotation or paraphrase from the published or unpublished work of others is duly acknowledged."

Signature: Date: September 25th, 2014

ABSTRACT

The recent financial crisis has renewed interest in the role credit plays, particularly when granted by the banking sector, to amplify the economic cycle. This thesis focuses on the credit supply side to study the informational efficiency of bank-based financial systems when granting credit to the economy. After a revision of the main areas of the literature that are devoted to such purpose, we set the behavioral economics and finance as a conceptual framework for our research. Thus, we firstly discuss the limits to apply the classic paradigm in financial markets, the efficient market hypothesis, to bank-based systems, and offer an alternative approach in three steps, based on the behavioral literature. Then, we implement an experimental research to test the first step. The experiment consists of a business simulation game designed to replicate the basics of a bank to set its credit policies. The results are tested against the participants' profiles in terms of overconfidence and prospect theory, to determine whether these behavioral biases might explain different credit policies across banks. Finally, we offer a theoretical model to analyze the second and third steps in the behavioral approach. Assuming some banks are run by too optimistic managers, the model shows how rational banks would herd to follow their biased competitors, and describes the limits of arbitrage in the industry that would prevent informational efficiency to be restored.

RESUMO BREVE

A recente crise financeira renovou o interese no papel xogado polo crédito, en particular bancario, na amplificación do ciclo económico. Esta tese céntrase no lado da oferta ao obxecto de estudar a eficiencia informativa dos sistemas bancarios cando conceden crédito á economía. Tras unha revisión das principais áreas da literatura centradas en dita cuestión, fixamos a economía e finanzas conductuais como marco conceptual da nosa investigación. Deste xeito, debatemos primeiro sobre as limitacións para aplicar a hipótese do mercado eficiente, paradigma clásico nos mercados financeiros, aos sistemas bancarios, e suxerimos un enfoque alternativo en tres pasos, baseado na literatura conductual. Logo, poñemos en práctica unha investigación experimental ao obxecto de testar o primeiro paso: un xogo de simulación deseñado para replicar o esquema básico no que un banco establece as súas políticas de crédito. Os resultados son contrastados cós perfís dos participantes en termos de exceso de confianza e a teoría prospectiva, para determinar se ditos sesgos poderían explicar diferentes políticas de crédito entre bancos. Para rematar, ofertamos un modelo teórico para analizar o segundo e terceiro paso. Asumindo que algúns bancos son dirixidos por xestores optimistas de máis, o modelo mostra como os bancos racionais seguirían aos seus sesgados competidores, e describe os límites da arbitraxe na industria que impedirían restablecer a eficiencia informativa.

RESUMEN BREVE

La reciente crisis financiera ha renovado el interés en el papel que juega el crédito, particularmente bancario, para amplificar el ciclo económico. Esta tesis se centra en el lado de la oferta para estudiar la eficiencia informativa de los sistemas bancarios a la hora de conceder crédito a la economía. Tras una revisión de la literatura centrada en dicho objeto, establecemos la economía y finanzas conductuales como marco conceptual de nuestra investigación. Asi, comentamos en primer lugar los límites para aplicar la hipótesis del mercado eficiente, paradigma clásico en los mercados financieros, a los sistemas bancarios, y ofrecemos un enfoque alternativo en tres pasos que se basa en la literatura conductual. Después, llevamos a cabo una investigación experimental para testar el primer paso: un juego de simulación diseñado para replicar el esquema básico en el que un banco establece sus políticas de crédito. Los resultados se contrastan con los perfiles de los participantes en términos de exceso de confianza y la teoría prospectiva, para determinar si estos sesgos podrían explicar las diferentes políticas de crédito. Por último, ofrecemos un modelo teórico para analizar los pasos segundo y tercero. Asumiendo que algunos bancos tienen gerentes demasiado optimistas, el modelo muestra cómo los bancos racionales seguirían a sus competidores sesgados, y describe los límites del arbitraje en la industria que impedirían restaurar la eficiencia informativa.

RELEVANT ACRONYMS

AMH: Adaptive Market Hypothesis
BAPM: Behavioral Asset Pricing Model
BF: Behavioral Finance
BPT: Behavioral Portfolio Theory
BV/MV: Book value to market value
CAPM: Capital Asset Pricing Model
CPT: Cummulative Prospect Theory
d/P: Dividend yield
DDM: Dividend Discount Model
DJIA: Dow-Jones Industrial Average index
E/P: Earnings yield
EMH: Efficient Market Hypothesis
EMM: Efficient Markets Model
EUT: Expected Utility Theory
GMM: Generalized Method of Moments
CCAPM: Consumption CAPM
IPO: Initial Public Offering
M&A: Mergers and Acquisitions
NPL: Non-performing Loans
NPT: Normalized Prospect Theory
OC: Overconfidence
PCA: Principal Component Analysis
P/E, PER: Price to Earnings ratio
PT: Prospect Theory
SEO: Seasoned Equity Offerings

For bibliographic references cited in the text, the first time a reference appears in a Chapter it is identified using all authors' names (e.g., Jorda, Schularick and Taylor, 2011) when there are up to three authors or (Brunnermeier et al., 2009) when there are four or more authors. Subsequent citations in the same Chapter are in the form (Jorda et al., 2011) when there are three or more authors. A list in alphabetical order of all bibliographic references cited in the Doctoral Thesis is provided at the end.

TABLE OF CONTENTS

INDEX OF TABLES

INDEX OF FIGURES

"Most increases in the supply of credit do not lead to a mania, but nearly every mania has been associated with a rapid growth in the supply of credit"

Ch. Kindleberger, 'Manias, Panics and Crashes'.

INTRODUCTION

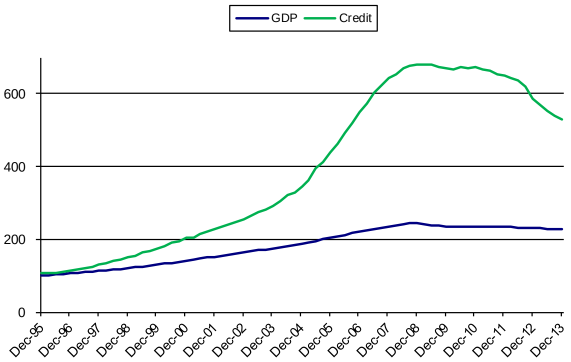
The worldwide financial meltdown of 2007–2008 and the sovereign debt crisis that followed afterwards in the Eurozone persuaded academics and economic authorities to reassess our views about some aspects of the functioning of market economies. Topics that were reviewed include the nature of economic cycles, the effectiveness of monetary policies, the role of derivatives, the effectiveness of banking regulation, and others. Thus, in regards to the financial meltdown, four major factors are cited to have caused it (Bean, 2010): the use of derivatives on a massive scale, a long period of low interest rates, the imbalances of globalization, and credit growth. Derivatives and structured securities such as collateralized debt obligations (CDOs) and credit default swaps (CDS) increased the risk appetite of investors and reduced their risk perception. Monetary policies from 2002 to 2006 have been criticized for being too loose, particularly in the U.S. and the Eurozone. Current account imbalances were at historic levels then and they were of counterintuitive sign, with capital flowing from the high-growing emerging countries to the aging, stagnant Western economies.

However, the factor that has received most attention from researchers is perhaps credit. The episode renewed the interest in the role credit plays in economic cycles, leading to a revival of classic works by authors such as Charles Kindleberger and Hyman Minsky, among others. Indeed, the good performance of western economies during the years before the Great Recession was largely fueled by credit, feeding real estate bubbles that would come to a dramatic end with the financial crisis. Overconfidence made economic agents believe this time was different and good times would last forever. Perceived risk decreased and a higher leverage followed. In consequence, the ratio of financial liabilities to GDP between 1995 and 2007 rose in countries like the U.K. from 128% to 213%, and multiple housing booms developed simultaneously during the same period in distant countries as the U.S., Ireland, Spain, Russia, Singapore, China or the Arab Emirates.

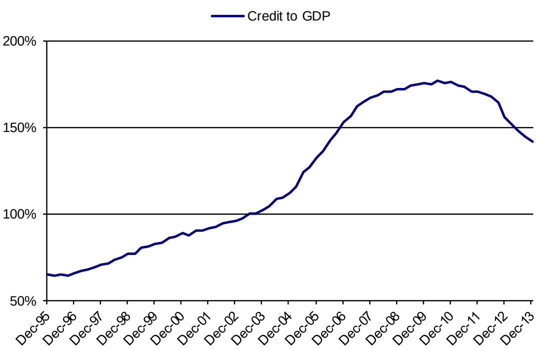
Jorda, Schularick and Taylor (2011) show that higher rates of credit growth relative to GDP tend to be followed by deeper recessions and slower recoveries. In economies where the weight of the banking sector is not much relevant, the ratio of bank lending to GDP often tends to remain low. For instance, in the U.S., from the 1950s to 1995, the ratio ranged from 7% to 14% (Himmelberg and Morgan, 1995). In bank-based financial systems, however, this ratio is often much higher and rose aggressively during the last crisis. In Spain, for instance, by mid 1990s the ratio was about 60% while it soared by 2009 to 175% —see charts a and b of Figure 0.1 below. Credit to households and institutions from 1995 to 2008 provided by the Spanish banking sector boosted from 271 to 1,870 billion euros, almost seven times higher. During the same period, the GDP rose 58%.

FIGURE 0.1 – Total credit, credit ratio to GDP and delinquency ratio in Spain

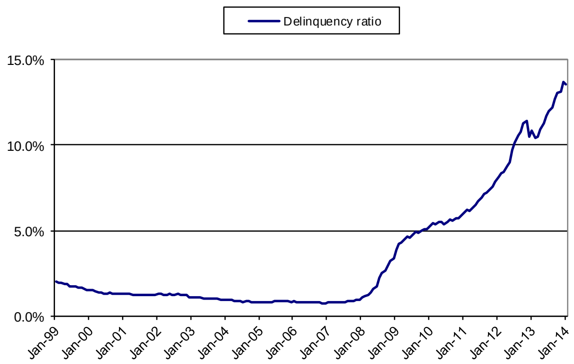
(a) Credit to households and firms. Spain, 1996 - 2013
Sources: BdE, INE



(b) Credit to GDP. Spain, 1996 - 2013
Sources: BdE, ECB



(c) Delinquency ratio (total). Spain, 1999 - 2014
Source: INE



Source: Own elaboration from BdE, ECB and INE

In addition, Reinhart and Rogoff's (2011) historical analysis of financial distress episodes confirm two other facts. The first one evidences that private debt surges are a recurring antecedent to banking crises. The increased leverage of the economy during good times often lead to episodes of financial distress in recessive periods: delinquency ratios on loans and other credit instruments soar and bank profits become losses. Take for instance again the case of Spain, where by December 2007 only 0.93% of the credit granted to families and firms were bad loans, whereas by January 2014 the average delinquency ratio amounted 13.58% —see Figure 0.1.c. Similar rates in market-based systems like the U.S., for instance, were only observable in credit cards and student loans, while on mortgages and auto loans the average delinquency ratio barely exceeded 5%.

The effects of the financial meltdown of 2007 and 2008 over the banking sector were devastating, both in the U.S. and the Eurozone. The list of banks that were filed for bankruptcy, declared insolvent, liquidated, taken over by another private bank, received financial aid by a governments, or were nationalized is extremely long: it would include the largest American investment banks (e.g., Lehman Brothers and Merrill Lynch) as well as commercial banks (e.g., Citigroup), the largest commercial banks of several European countries (e.g., HBOS, Fortis, Dexia, RBS, UBS, Bankia), banks as well as insurance companies and brokerage firms (e.g., AIG, MF Global), and private as well as public or government sponsored entities (e.g., FNMA and FHLMC, commonly known as Fannie Mae and Freddie Mac) and foundations (e.g., Spanish savings banks).

The second fact pointed out by Reinhart and Rogoff (2011) is that banking crises often precede (and predict) sovereign debt crises. Indeed, they confirm a strong link between banking crises and sovereign default across the economic history of many countries. A link manifested as well in the recent Eurozone crisis as a negative feedback effect between sovereign debt and the balance of the private banks. Thus, banking crises that often follow after periods of indulgent lending practices have harmful consequences over not only the stability of the banking sector itself, but over the stability of the whole economy, too.

Following these pieces of evidence, the analysis of the efficiency of the banking sector when granting credit to the economy reveals to be an interesting field of research. In what follows we summarize the main purpose of this thesis, as well as the approach we followed in our research. This is done in four instances. Firstly, we determine the object of study. Secondly, we enumerate the main objectives that were pursued. Thirdly, we specify the methodology implemented. Fourth, we describe the structure of the thesis and summarize the contents of each chapter.

Object of study

Since credit crises may be associated to both credit-supply and credit-demand effects, we must clarify in first instance that this doctoral research focuses on the credit supply side, in order to provide an alternative means to analyze the causes behind a credit boom. Credit booms would reveal either a banking sector unable to make a proper evaluation of credit demand and the risks involved or, at least, a banking industry where some participants were aware of those risks, but who chose to follow their competitors in order not to lose market share or to reduce the risk of underperformance.

Thus, the object of study of this thesis is the efficiency of bank-based financial systems when granting credit to the economy. Consequently, the scope of our research are the retail credit markets, defined as the transactions between retail banks and their customers that involve some sort of credit granted (loans, mortgages, etc.), which are broadly funded with deposits from other clients. The main innovation is the conceptual framework we use for such purpose: the behavioral economics and finance. In market-based systems, the classic approach to examine efficiency is the Efficient Market Hypothesis, EMH. However, we will see imperfect competition and informational asymmetries in bank-based systems would leave this approach without content. Some alternatives emerged to provide an interpretation of what determines how much credit banks should grant to borrowers —alternatives that will be reviewed as well. Notwithstanding, a first contribution of this thesis is to provide a behavioral approach to analyze the efficiency of bank-based financial systems, allowing to explain how behavioral biases by participants in the banking industry might explain credit cycles.

This behavioral approach allows to study the effects of behavioral biases by CEOs and employees in the industry over the credit policies implemented by the retail banks and their strategic behavior when they compete to grant credit to different niches of potential borrowers. That is indeed the main question we want to answer in this research: could it be that credit booms fueled by the banking sector are a manifestation of a herd behavior that appears as a consequence of different behavioral profiles and biases among participants in the industry? We provide a theoretical an experimental approach to answer such question.

We find this to be a relevant question that deserves to be answered. The academic research that followed the financial crisis has analyzed issues such as the incentives, securitization, and the risk-taking moral hazard by banks, but little has been done to interpret the role that human psychology might have had. This is puzzling, since the behavioral economics has identified and explained a wide range of anomalies in areas as diverse as health, education, energy, insurance, and public choice. In particular, the most productive and successful area has been behavioral finance applied to financial markets: the excessive volatility puzzle, the evidence of overreaction, underreaction and an excessive trading, the preference of investors for dividends, the equity risk premium, the recurrence of financial bubbles, etc.

Thus, we suggest to extend the insights of the behavioral economics and finance to the analysis of the informational efficiency in bank-based financial systems. This would complement the literature on credit bubbles by suggesting that the explanations already provided, such as the moral hazard and the role of incentives, could have been even more pervasive due to psychological biases. In addition, it would contribute to the open debate on questions such as the necessity to improve the macroprudential regulation (Brunnermeier et al., 2009) or the pros and cons of separating the monetary and credit functions by promoting a full-reserve banking system (Benes and Kumhof, 2012).

Objectives

The key goal of this thesis is to analyze the informational efficiency of retail credit markets through a behavioral approach. The main motivation is to provide a rationale that would explain how different behavioral biases by participants in the banking industry could explain an excessive lending by retail banks and a herd behavior among them. Such main goal may be dissected into several specific objectives. They follow in order below.

First, we intend to review the main conceptual frameworks that have been used to analyze the informational efficiency of financial markets generally speaking, and the banking sector in particular.

We wish to provide an insight on the different approaches that are used in both instances, and to interpret the obstacles that limit the application of the classic approach in financial markets —namely, the EMH— to the banking system.

Second, we seek to provide an extensive review of the behavioral economics and finance as a conceptual framework for our experimental and theoretical research. In particular, we intend to highlight the clash between the opposite views of rationalists and behaviorists in the scope of financial markets.

Third, we are in search of an alternative approach to test the informational efficiency of retail credit markets in a way akin to how efficiency is interpreted under the EMH in financial markets. Such alternative approach follows the behavioral literature to test market efficiency in financial markets, while it sidesteps the presence of informational asymmetries and imperfect competition within the banking industry that impede the extension of the EMH to bank-based systems.

Fourth, we seek to provide experimental evidence of the effects that behavioral biases might have over the credit policies implemented by the banks. In particular, in regards to the biases we focus on two relevant areas of the behavioral literature: the effects observed for individuals with different risk profiles, according to prospect theory, and different levels of overconfidence. In regards to the credit policies, we seek to trace the effects in terms of prices, volumes and quality of credit.

Fifth, we intend to provide a theoretical model that explains the behavior of banks of a different nature, some managed by excessively optimistic CEOs and others not, when they compete for potential borrowers to whom grant credit. Among the questions we seek to answer we may mention why and when rational banks would herd to follow their biased competitors, the effects of behavioral biases in banking competition along the economic cycle, and the lessons to be learned in the debate for an enhanced macroprudential regulation.

Methodology

We intend to extend the insights of the behavioral economics and finance to the analysis of the informational efficiency of the banking sector when granting credit to the economy. The purpose is to determine whether there is a rationale for human psychology —in particular, different behavioral biases by participants in the banking industry— to explain a herd behavior that amplifies the boom and busts of credit cycles. The motivation for it is twofold. On one hand, we have seen that relaxed lending practices often antecede banking crises, and these often precede sovereign debt crises as well. The recent episodes of the worldwide financial meltdown and the Eurozone crisis are good examples of it. On the other hand, the behavioral finance is the field that has been more successful in criticizing the tenets of market efficiency, but little has been done about combining human psychology and banking crises.

We proceed as follows. Firstly, we identify the conceptual frameworks in the literature that may contribute to our work. These are the theories of credit and banking efficiency, which compile the different approaches available to analyze the efficiency of the banking sector, the efficient market hypothesis, which is the classic paradigm to test efficiency in financial markets, and the behavioral finance, which is the area that has succeeded in providing an alternative interpretation to the EMH in financial markets.

Secondly, we focus on the behavioral finance as a conceptual framework in this research. Thus, we review the main behavioral biases and anomalies identified in the literature, with special attention on two areas of research: prospect theory and overconfidence.

Third, we introduce a behavioral approach to analyze the informational efficiency in retail credit markets. It only requires to apply the classic approach, summarized by Shleifer (2000), the behavioral finance uses to analyze the informational efficiency in financial markets. To such purpose, we firstly discuss the conditions under which this approach would be valid when applied to retail credit markets. This provided, the behavioral approach would consist of a stepwise procedure in three steps: whether participants in the industry exhibit behavioral biases that may conform a market sentiment, whether market sentiment could exhibit trends or predictable patterns, and whether there are limits of arbitrage in retail credit markets.

Fourth, in the core of this thesis, we provide a theoretical and experimental approach to answer those three questions in the stepwise approach. In particular, we implement an experimental research in order to test the first step, while we offer a theoretical model that explains how a herding behavior among rational and biased banks would induce a market sentiment along the cycle, and what would be the limits of arbitrage in retail credit markets that prevent efficiency to be restored.

The experimental research consists of two types of tests: on one hand, a set of questionnaires devised to determine the psychological profile, based on prospect theory and overconfidence, of a given respondent; on the other, a business simulation game designed to replicate in an experimental setting how banks grant credit to their potential borrowers, in order to obtain information about how much credit and at what price different subjects would grant, under conditions of uncertainty and risk. A total of 126 undergraduate and postgraduate students from University of A Coruna (UDC) completed both types of tests. The implementation of these tests to the same group of participants allows us to trace the connection between behavioral profiles and risk attitudes in the game. This would help us to test the first step in the so-called behavioral approach: whether participants in the banking sector may exhibit behavioral biases that may conform a market sentiment.

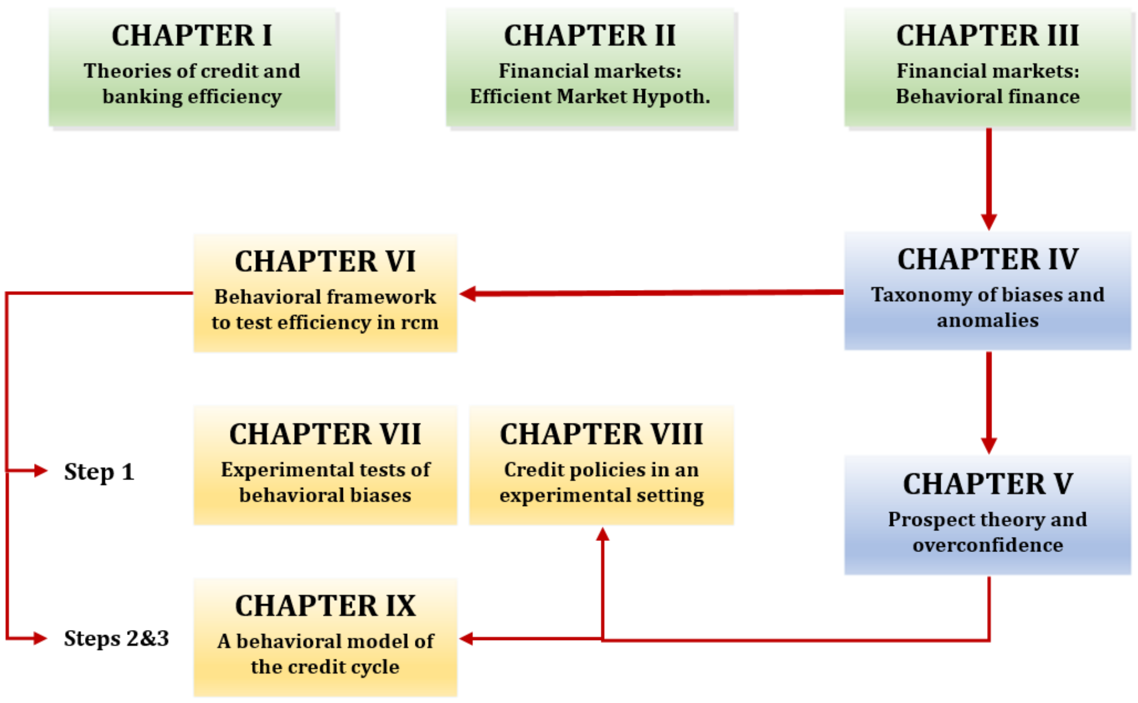
We propose, and calibrate, a series of independent variables for the behavioral profile of each participant, as well as a series of dependent variables representative of the credit policies they implemented in the experiment. We structure the basic premise in a series of hypothesis to be tested. The statistical techniques used to that purpose include univariate statistics (normality tests, interquartile range, etc.), bivariate statistics (correlations, ANOVAs, regressions) and multivariate statistics: multiple linear regressions (MLR), principal component analysis (PCA), cluster analysis and correspondence analysis. A summary of conclusions is eventually provided.

Steps two and three in the stepwise approach are tackled through a theoretical model. The basic hypotheses are, thereupon, that a herding behavior across participants in the industry might conform a market sentiment beyond fundamentals, and that the existence of limits of arbitrage would prevent efficiency in retail credit markets to be restored. To such purpose, we build a simple model of duopoly competition between banks of a different nature that shows how rational banks would herd to follow their biased competitors to grant excess credit during economic upswings. According to it, biased banks would lead the industry and unbiased banks herd under conditions we derive. Finally, we describe the limits of arbitrage that are implicit in the model. Then, we offer a dynamization of the model in order to provide an intuition of how the credit cycle would be amplified due to banking competition. A summary of conclusions is finally provided.

Structure of the thesis

The structure of the thesis is summarized in Figure 0.2 below.

FIGURE 0.2 – Structure of the thesis



Source: Own elaboration

The thesis is structured as follows. The main contents are presented in three parts plus a summary of results and a set of conclusions, followed by the references and appendices. Part I reviews the main conceptual frameworks identified in the academic literature that may contribute to analyze the informational efficiency of retail credit markets through a behavioral approach. These are the theories of credit and banking efficiency, the efficient market hypothesis, and the behavioral finance. Then, Part II extends our insights in behavioral finance and, in particular, overconfidence and prospect theory. Parts I and II will reveal convenient for the purposes of our research in Part III, where we offer an experimental research and theoretical model that provides a rationale for behavioral finance to challenge informational efficiency in bank-based systems as well. The main results of the dissertation, as well as a set of conclusions and guidance for future research are listed at the end.

Part I is formed by three chapters, each of them devoted to review a different conceptual framework to analyze efficiency in retail credit markets. There we interpret how efficiency of the banking sector is analyzed, how it is analyzed when it refers to market-based systems, and how behavioral finance has come to dispute the orthodoxy in regards to market efficiency.

Chapter 1 defines retail credit markets and goes on with the main theories of credit and banking efficiency. We identify the classic approach to analyze the efficiency of the banking sector. The review of the different theories and concepts of economic efficiency illustrates the way this approach differs to how efficiency is interpreted when analyzed in financial markets —which is described in Chapter 2. The chapter ends with some theories that interpret what determines how much credit banks should grant and to whom: the microeconomics of credit —that is, some theories on bank decision making when granting credit to individual borrowers— as well as the macroeconomics: some arguments that have already been suggested by researchers to justify how retail credit markets could malfunction.

Chapter 2 describes the theoretical foundations of the efficient market hypothesis in financial markets. Firstly, we describe the essential role financial markets play in capitalist economies, which requires a pricing mechanism that provides an efficient reflection of information about fundamental values into prices. We then provide an extensive insight on the theoretical foundations of the EMH —namely, the role of expectations, information, and the discount factor. Then it follows a discussion on the testability of the EMH. We enumerate several reasons why researchers have criticized the validity of the EMH as a refutable hypothesis, including the two alternative definitions of the EMH and the joint hypothesis problem. The analysis is completed with a taxonomy of the different approaches suggested for empirically testing the three forms of the EMH (weak, semi-strong and strong forms) and the most relevant results that have been obtained in the academic literature.

Finally, Chapter 3 introduces the theoretical foundations of the behavioral economics and finance. Faced with the postulates by standard finance of rational expectations and market efficiency, the behavioral economics suggests instead a wider approach based on a combination of social sciences, including psychology, sociology and demography. In line with this, the behavioral finance deals with the influence of psychology in financial decision making and financial markets. Thus, we firstly review the groundbreaking research on behavioral economics and finance. This would also help us familiarize with the myriad of biases and anomalies that pervade decision making and challenge the postulates of standard finance —biases and anomalies to be extensively reviewed in Part II. The chapter ends with a brief summary of the most recent theories developed by behaviorist researchers in areas like decision theory, financial markets, corporate finance, debiasing, and others.

Part II is formed two chapters, both devoted to provide a deeper insight on different aspects of the behavioral finance that will reveal essential for the theoretical and experimental research in Part III.

Chapter 4 presents an original taxonomy and extensive review of the most relevant biases and anomalies. The taxonomy synthetizes the literature to provide a comprehensive approach in two broad categories: psychological biases and behavioral consequences. Psychological biases are classified into four groups: heuristics and biases, framing, valuation/errors-of-preference and social factors. Behavioral consequences may refer to decision effects (related to individuals) or to market anomalies. The subsequent sections of Chapter 4 are devoted to enumerate and analyze the most relevant of those biases and consequences, as well as the main contributions in the literature about them. Our goal will be to choose two specific areas on which to focus our research in Part III.

Chapter 5 reviews these two areas more extensively, namely overconfidence and prospect theory. We begin with a vindication of our choice: they are two of the most-well studied areas in behavioral finance, both concepts have been suggested to explain a risk-seeking behavior by investors, and they could help explain as well how misperceptions by participants in the banking sector might have led them to engage in unsound credit policies. Then, the chapter provides further insight into prospect theory and overconfidence with the focus on several aspects that will be required in the experimental research in Part III —in particular, the different measures available and how to calibrate the parameters at the individual level through a set of questionnaires.

Part III is devoted to provide a rationale for psychology to challenge informational efficiency in bank-based systems. The analysis comes in three instances, divided in four chapters.

Chapter 6 introduces an alternative to analyze the efficiency of bank-based systems. On one hand, we have the classic approach in market-based systems, the EMH. However, imperfect competition and informational asymmetries in bank-based systems would leave this approach without content. On the other, we have the stepwise procedure behaviorists have followed to test market efficiency considering the two elements that might challenge it: market sentiment and limited arbitrage. The approach we suggest is simply to apply the stepwise approach to retail credit markets. To such purpose, we firstly discuss the conditions under which it would be valid. First, it would be a plausible alternative to test only the informational efficiency side of EMH, interpreted as whether through banking intermediation information is transmitted efficiently in the EMH sense. This way, the approach sidesteps the analysis of the allocative and operational efficiencies —which in bank-based systems are often affected by imperfect competition and informational asymmetries. Second, the approach would be valid only for the aggregate credit market. This provided, the so-called behavioral approach would consist of a three-step process to determine (a) whether CEOs and employees in the industry exhibit beliefs that, based on heuristics and other forms of bounded rationality, could conform a market sentiment; (b) whether market sentiment could exhibit trends or predictable patterns; (c) whether there are limits of arbitrage in retail credit markets. Finally, Chapter 6 ends with a research agenda to suggest various ways the stepwise approach might be empirically tested. Of the suggestions there provided, Chapters 7 to 9 focus on the effects of prospect theory and overconfidence.

The experimental research in Chapters 7 and 8 aims to test the first step in the stepwise approach. In particular, we focus on the effects of prospect theory and overconfidence, analyzed in detail in Chapter 5. Two broad questions are to be answered. First, Chapter 7 seeks to identify the existence of these behavioral biases among a series of participants in an experimental test. Second, whether these biases could feed, among that same set of respondents, a risk-seeking behavior in a simulated credit market —which is analyzed in Chapter 8. The experimental sessions took place in the Faculty of Business and Economics at UDC during October, 2013. A group of 126 undergraduate and postgraduate UDC students participated in the experiment divided in five sessions. Participants in the same session completed all tests at the same time, each respondent in a separate computer.

Chapter 7 deals with the description of the behavioral tests in the experiment, how they were designed, variables to be measured, hypotheses to be tested (regarding the effect of several priors over those variables), participants in the experiment, data and results obtained. The statistical analysis provided describes the behavioral tests in first instance: how they were designed and variables to be measured. Then it compares the results of the tests with the standard results in the literature, in order to confirm the validity of the tests implemented. Lastly, the hypothesis to be tested are introduced and the results obtained are interpreted. Chapter 8 deals with the strategy game designed to infer how the same 126 participants would behave when granting credit to the economy. For such purpose, they competed for a prize in a simulation game where they played the role of a bank granting credit to their customers under conditions of uncertainty and risk about the economic environment. The strategies they implemented resulted in three types of indicators (price, quantity and quality of credit) for the hypotheses to be tested. Chapter 8 includes a description of how the experiment was designed, the basics of the game, the hypotheses to be tested (regarding the effect of the behavioral variables over the outcomes of the game), how the experiment was implemented, data and results obtained.

The combination of the research in Chapters 7 and 8 allows us to test the possible relationship between behavioral profiles and risk attitudes in the game, in order to determine whether the behavioral biases identified among participants in the experiment could feed a risk-seeking behavior in a simulated credit market. Then, Chapter 9 eventually provides a theoretical model that follows the second and third steps in the stepwise approach to determine how a duopoly of banks would compete to grant credit. The model provides two developments starting from the assumption that some banks in the industry might be biased in terms of overconfidence and excessive optimism —particularly during the upswing of the economic cycle.

In the first development, the second and third steps in the stepwise approach are analyzed: how would a duopoly of a rational and a biased bank compete when granting credit to the economy, whether herding strategies would appear, and whether limits of arbitrage in the industry are identifiable. We build a model of duopoly competition among banks to show that behavioral biases by participants in the industry explain how a credit bubble is fueled. According to it, biased banks would lead the industry and unbiased banks herd under conditions we derive. Finally, we describe the limits of arbitrage that are implicit in the model.

The second development would contribute to explain how the credit cycle is amplified due to banking competition. We find pessimism would not be a powerful driver of credit cycles: instead, it is the euphoria during large upswings what seeds the next crunch. Finally, we offer a dynamization of our model to provide further insight on how boundedly rational competition would amplify the credit cycle. In addition, the model makes some predictions that are consistent with the empirical observation —in particular, that the effects of the behavioral biases are more pervasive during upswings and the lower the quality of the niche market.

Main results and conclusions. Finally, the presentation of the contents of this thesis ends with a disclosure of the main results obtained, as well as a set of conclusions and suggestions for future investigation. The appendices and bibliographic references are relegated to the end.

All together, the research provided in this doctoral thesis could be a relevant contribution to identify the possible weaknesses of the banking industry, and hence to promote a complementary regulation —particularly on macroprudential regulation and the role of central banking. Our model would show how behavioral biases might guide retail credit markets and why limits of arbitrage would imply bank-based systems are less likely to be informationally efficient than market-based ones.

Would the behavioral approach introduced in this doctoral thesis provide further evidence on the pervasiveness of behavioral biases in the banking industry, then banking regulation should account for it. However, the solution is not more regulation per se, but better and different regulation. The behavioral approach we use would come in support of countercyclical regulation; how to implement it, however, is beyond the scope of this thesis. Moreover, we must consider the possibility that the authorities, just like the private banks, might fail as well in their purpose to apply the required counterbalancing policies.

PART I. GENERAL REVIEW OF THE MAIN FRAMEWORKS ON INFORMATIONAL EFFICIENCY OF RETAIL CREDIT MARKETS

SUMMARY OF PART I

Efficiency is a recurrent concept in Economics, as it applies to a multitude of areas. However, it may be misleading as it has multiple interpretations, too: economic efficiency, market efficiency, social efficiency, business efficiency, Pareto efficiency, technical efficiency, allocative efficiency, informational efficiency… The perception that a rapid growth in the supply of credit above economic fundamentals and, consequently, an inefficient performance by financial institutions might have been a key factor behind the financial crisis, must be bounded to one of those scopes and interpreted in such terms.

The aim of Part I is to provide a literature review of the main theories that analyze the efficiency of the financial system generally speaking, and of the banking industry in particular. These are the theories of credit and banking efficiency, the efficient market hypothesis (EMH), and behavioral finance. Then, Part II will extend our insights in behavioral finance and, in particular, overconfidence and prospect theory, since we will be using a behavioral approach for the theoretical and experimental analysis in Part III. Thus, the review provided in Parts I and II will reveal convenient for the purposes in Part III, as the theories described in the former are helpful to understand our contributions in the latter.

Part I is organized as follows. In Chapter 1 we define retail credit markets and go on with the main theories of credit and banking efficiency. Chapter 2 describes the theoretical foundations of the efficient market hypothesis in financial markets and how behavioral finance challenges them. Finally, Chapter 3 introduces the theoretical foundations in behavioral economics and finance, which will later be extended in Part II.

CHAPTER 1. THEORIES OF CREDIT AND BANKING EFFICIENCY

1.1. INTRODUCTION

Are bank-based financial systems efficient when providing credit to the economy? Trying to answer such question requires to address several issues in first instance. First, we must delimit the scope of our analysis. What are bank-based financial systems? How do banks grant credit to the economy? How do this industry differ from credit markets in market-based financial systems? For such purpose, we will define retail credit markets and provide an example to illustrate. Second, we identify the classic approach in the literature to analyze the efficiency of the banking sector. A brief review of the different theories and concepts of economic efficiency will suffice to illustrate why this approach differs to how efficiency is interpreted when analyzed in financial markets —which is described in Chapter 2.

Consequently, to answer whether banks are efficient when granting credit to the economy, we must review the different theories that interpret what determines how much credit banks should grant and to whom. This is what we will do in third instance. In particular, we will analyze both the micro and the macroeconomics of credit: that is, some theories on a bank decision making to extend credit to individual customers, as well as some other arguments that were proposed to justify how retail credit markets could malfunction.

The chapter is organized as follows. Section 1.2 is devoted to delimit and define retail credit markets, followed by a description of the Spanish banking industry as an example. Section 1.3 introduces the analysis of economic efficiency in the banking sector according to different approaches in the literature. Section 1.4 introduces different theories of credit in the literature about how banks determine how much and to whom credit is granted.

1.2. RETAIL CREDIT MARKETS

Financial systems consist of the set of institutions, markets and resources, whose primary purpose is to convey savings from savers to investors (Parejo et al., 2011). A traditional classification is to distinguish between bank-based and market-based financial systems. Following Xiao (2011), in bank-based systems most firms' external funds are provided by banks with which they have long-term relationships, whereas banks' main duty is to take deposits and lend directly to firms and individuals. Market-based systems are characterized instead by firms that expect financial markets to meet their financial needs. Bonds play here the largest role in short term financing, and firewalls exist to separate the different types of financial services —taking deposits and granting loans on one hand, underwriting and trading equities on the other.

The Eurozone and Japan would be better described as bank-based systems —as opposed to the U.K. and the U.S. (Levine, 2002; Allen, Chui and Maddaloni, 2004). Since the 19th century, two competing views have alternatively argued that bank-based systems are better at mobilizing savings, identifying good investments, and exerting corporate control, whereas market-based systems would be better in allocating capital, providing risk-management tools, and mitigating the problems of too-big-to-fail banks (Levine, 2002). The scope of analysis in this thesis will be the bank-based systems and, in particular, to set a behavioral approach to analyze whether the banking industry may be efficient when providing credit to the economy. Here, the efficiency concept we follow intends to be interpreted in a way akin to the Efficient Market Hypothesis in market-based systems.

Therefore, we set our framework to be an informational efficiency analysis of the credit policies implemented by retail banks. We delimit retail banking as the transactions between banks and their customers (households and companies), and credit policies as the prices and volumes of credit banks set on loans and other credit instruments they provide to their clients. Consequently, we define retail credit markets[2] as those transactions between retail banks and their clients that basically involve some sort of credit granted. These include personal loans, mortgages, credit accounts, credit cards and other credit instruments, which are broadly funded with deposits from other customers.[3]

Take the Spanish banking industry as an example. In Spain there are four types of institutions:[4] banks; savings banks and CECA[5] and credit cooperatives; other credit institutions (EFC and EDE);[6] and the Government agency *Instituto de Crédito Oficial*, ICO. Banks and savings banks, which we will refer to as the banking system, represent the large majority of the industry. Table 1.1 summarizes the assets in the consolidated balance of these institutions by March 2011. According to it, the banking system granted 94.3% of all credits and loans to residents in Spain and 99.0% to those residents abroad the EU.

---

[2] From here onwards we will refer to retail credit markets, retail banking and bank-based system as equivalent concepts.
[3] Obviously, credit institutions often deal with a broader list of activities others than credit. For instance, the banking regulation in Spain (*Ley 3/1994, de 14 abril; Ley 44/2002, de 22 de noviembre*) considers the following list of 15 typical activities by credit institutions: deposit taking; credits and loans, including consumer credit, mortgages and commercial credit; factoring; leasing; payment services; credit cards and travel checks; endorsements and guarantees; intermediation in interbank markets; dealing and brokerage; securities underwriting; services on corporate management, merges and acquisitions; wealth management; securities depository; business reports; safe custody services.
[4] Ley 3/1994 and subsequent modification Ley 44/2002.
[5] The Spanish *Cajas de Ahorro* (savings banks) are clustered in the organization CECA, *Confederación Española de Cajas de Ahorro,* which beyond providing representation services and other facilities to their members it may also act as a savings bank. Savings banks and CECA implemented in recent years a process of transformation into banking institutions, separating their financial activities from those merely associative. In the case of the CECA, this meant the launching of bank Cecabank in 2012.
[6] The *Establecimientos Financieros de Crédito* (EFC) include former institutions on leasing and factoring services. The *Entidades de Dinero Electrónico* (EDE) are institutions whose primary activity is the issuance of means of payment (Parejo et al., 2011).

TABLE 1.1 – Consolidated balance of credit institutions in Spain

Consolidated Balance (ASSETS)

(million euros and percentage; March 2011)

ASSETS	*CREDIT INSTITUTIONS* TOTAL	*Banking System* Volume	%	*EFC & EDE* Volume	%	*ICO* Volume	%
a) Residents in Spain	2,790,006	2,640,220	94.6%	46,894	1.7%	102,892	3.7%
Credits and loans	2,161,804	2,038,519	94.3%	43,939	2.0%	79,346	3.7%
Securities others than shares	522,910	496,594	95.0%	3,012	0.6%	23,304	4.5%
Investment fund shares	0	0		0		0	
Shares	105,380	105,105	99.7%	34	0.0%	241	0.2%
b) Residents in other EU countries	164,507	160,219	97.4%	3,693	2.2%	595	0.4%
Credits and loans	102,009	97,797	95.9%	3,680	3.6%	532	0.5%
Securities others than shares	41,111	41,050	99.9%	0	0.0%	61	0.1%
Investment fund shares	6	6	100.0%	0	0.0%	0	0.0%
Shares	21,382	21,367	99.9%	13	0.1%	2	0.0%
c) Rest of the World	218,373	216,297	99.0%	765	0.4%	1,311	0.6%
d) Unclassified	273,419	271,328	99.2%	1,915	0.7%	176	0.1%
TOTAL ASSETS							

Source: Parejo et al. (2011)

As mentioned in the Introduction, before the worldwide financial meltdown of 2007 and 2008 high rates of credit growth relative to GDP were observed in most advances economies, but with a higher exposure in economies where the weight of the banking sector was relevant. Thus, one of the effects of the financial meltdown was the impact over some of the largest investment and commercial banks, both in the U.S. and Europe (Lehman Brothers, Merrill Lynch, Citigroup, Fortis, Dexia, RBS, UBS, etc.), which in some cases led to the demise of the company.

In the case of the Spanish sector, credit to households and institutions boosted a 700% from 1995 to 2008 while, by the same period, GDP rose 58%. Then, following the global financial crisis after 2008, the delinquency ratio started to soar from 0.93% by December 2007 to 13.58% by January 2014 (recall Figure 0.1). In consequence, the Spanish banking sector experienced a large restructuring process to help them overcome the effects of the crisis. This process manifested itself through several public interventions, merges and acquisitions, but the most relevant fact was the *de facto* transformation of savings banks into banks.[7] Following IMF (2012), Table 1.2 summarizes the restructuring process in the Spanish banking sector after 2009.

[7] The analysis of the restructuring process of the Spanish banking sector —and of savings banks in particular— is beyond the purposes of this thesis. Notwithstanding, let us mention that this transformation of savings banks into regular banks was conducted basically as follows: each savings bank launched a new bank of its property to operate their financial activities through it, while the former savings bank was transformed into a foundation. By 2014 the only exceptions are two, namely, *Caixa Ontinyent* and *Colonya, Caixa Pollença*. Both are minor, local entities that maintain the status of savings banks today.

TABLE 1.2 – Spain: Consolidation of the Banking Sector

2009	2010	2011	2012	2013
Banco Santander *Banesto*	Banco Santander *Banesto*	Banco Santander *Banesto*	Banco Santander *Banesto*	Banco Santander
BBVA Caixa Sabadell Caixa Terrassa Caixa Manlleu	BBVA Unnim	BBVA Unnim	BBVA	BBVA
La Caixa Caixa Girona Cajasol Guadalajara Caja Navarra Caja Burgos Caja Canarias Banco de Valencia	La Caixa Cajasol-Guadalajara Banca Cívica Banco de Valencia	La Caixa Banca Cívica Banco de Valencia **21.11.2011**	Caixabank Banco de Valencia	Caixabank
Caja Madrid Bancaja Caja Insular Canarias Caixa Laietana Caja Ávila Caja Segovia Caja Rioja	BFA - Bankia	BFA - Bankia	BFA - Bankia **9.05.2012**	BFA - Bankia
Caixa Catalunya Caixa Tarragona Caixa Manresa	Catalunya Caixa	Catalunya Caixa	Catalunya Banc **17.12.2012**	Catalunya Banc
Caixa Galicia Caixanova	Nova Caixa Galicia	Nova Caixa Galicia	Novagalicia Banco **17.12.2012**	NGB (ABANCA) **18.12.2013**
Banco Sabadell Banco Guipuzcoano CAM Banco Gallego	Banco Sabadell CAM Banco Gallego	Banco Sabadell Banco Gallego	Banco Sabadell Banco Gallego	Banco Sabadell
Banco Popular Banco Pastor	Banco Popular Banco Pastor	Banco Popular Banco Pastor	Banco Popular	Banco Popular
Unicaja Caja jaen Caja Duero Caja España	Unicaja Ceiss	Unicaja Ceiss	Unicaja	Unicaja
BBK Cajasur Caja Vital Kutxa	BBK Caja Vital Kutxa	Kutxa Bank	Kutxa Bank	Kutxa Bank
Caja Murcia Caixa Penedés Caja Granada Sa Nostra	Banco Mare Nostrum	Banco Mare Nostrum	Banco Mare Nostrum	Banco Mare Nostrum
Ibercaja CAI Caja Círculo Caja Badajoz	Ibercaja CAI Caja Círculo Caja Badajoz	Ibercaja Caja 3	Ibercaja	Ibercaja
Bankinter	Bankinter	Bankinter	Bankinter	Bankinter
Cajastur CCM Caja Extremadura Caja Cantabria	Cajastur Caja Extremadura Caja Cantabria	Liberbank	Liberbank	Liberbank

Notes: Banks coded in red were intervened; banks in green were part of the institutional protection scheme

Source: IMF (2012), years 2012 and 2013 own elaboration

According to IMF (2012), the industry was concentrated by 2011 in only ten groups, four banks (Santander, BBVA, Popular and Sabadell) and six former savings banks (Caixabank, Bankia, Unicaja, Catalunya Banc, Novagalicia Banco and Kutxa Bank). These ten groups held the large majority (79.2%) of the assets in the industry,[8] with the other 20.8% corresponding to small private banks (11.9%), all other non-foreign banks (5,1%) and the cooperative sector (3,7%). This concentration was the result of merges and acquisitions of a total sum of more than fifty banks and savings banks that existed before 2009. Some of them remain intervened or part of the institutional protection scheme to date.

1.3. ANALYSIS OF ECONOMIC EFFICIENCY IN THE BANKING SECTOR

The way efficiency is interpreted when applied to bank-based financial systems differs to how it is analyzed in market-based ones. The reason is that the approach used in financial markets, the EMH —i.e., how agents analyze information to price securities, and whether through this process information is transmitted efficiently— collides with the classic paradigm of banking theory: market microstructure and asymmetries of information. Thus, Sections 1.3 and 1.4 are devoted to introduce different theories about how banks provide credit to the economy and banking efficiency. In what follows we first make a short review of the literature on banking efficiency.

In perfectly competitive markets we expect inefficient firms to be driven out by the efficient. However, the empirical finding that substantial inefficiencies often arise leads to some interpretations. Could imperfect competition be a consequence of regulatory limits on competition or not perfectly integrated markets? Could it be that an oligopolistic structure makes banks implement collusive practices? May it be that it is efficiency what determines both the market structure and performance of the firms, so the positive relationship between market power and performance (profits) is spurious? There is an extensive research on industrial organization that finds a positive statistical relationship between profitability and market structure (Berger, 1995). Although this result is generally accepted, there is no agreement on the hypothesis which generates it (Fiordelisi, 2004). Two types of theories were suggested to explain this finding: Market Power hypotheses —including the structure-conduct-performance (SCP) and relative-market-power (RMP) models— and Efficient Structure (ES) hypotheses.

1.3.1. Efficient structure vs. Market power paradigms

The *Structure-Conduct-Performance* (SCP) paradigm interprets performance as a result of the exogenous structure of the market which influences bank's conduct (Mensi and Zouari, 2010). The SCP model

[8] These ten groups were Banco Santander (18.9% of the assets), BBVA (14.9%), Caixabank (12.1%), BFA-Bankia (11.9%), Banco Sabadell (5.6%), Banco Popular (5.5%), Unicaja (2.7%), Kutxa Bank (2.6%), Catalunya Banc (2.5%) and Novagalicia Banco (2.5%), In addition, the assets abroad by Banco Santander and BBVA, which are larger than their domestic interests in both instances, were not considered for the purposes of this classification.

assumes that a higher concentration allows banks to implement collusive practices, like setting lower deposit rates and higher loan rates, and consequently gain substantial profits (Bain, 1951; Stigler, 1964). An alternative paradigm is the *Efficiency Hypothesis* (Demsetz, 1973), which interprets market power and performance of banks as a consequence of their efficiency levels: banks which operate more efficiently than their competitors will gain higher profits resulting from lower costs, hence they hold an important share of the market. Consequently, the positive relationship between market power and performance is only spurious, what generates them both is efficiency.

Both paradigms have been explored following different hypotheses. Smirlok (1985), subscribing to the efficiency hypothesis, considers market share as a proxy for efficiency. According to this interpretation, the efficiency hypothesis would prevail when a significant positive correlation between market share and profitability is detected (Mensi and Zouari, 2010). Other authors instead (e.g., Shepherd, 1986; Berger, 1995) advise against the use of such proxy and recommend a direct measure of efficiency. Shepherd (1986), for instance, considers the direct source of market power is the domination of participants over the individual market. Hence, it follows the emergence of a theory related to the SCP model, the *Relative Market Power* (RMP) hypothesis: only banks with a larger market share and well-differentiated products are able to exercise market power to determine prices and make supernormal profits (Berger, 1995). Nevertheless, the results may be ambiguous: a bank with a strong position in the market may either reinforce its domination over the market or achieve a higher efficiency (Mensi and Zouari, 2010). Thus, a particular case of market power hypothesis is the *Quiet Life* hypothesis (Hicks, 1935): a bank with a large market share is less centered on efficiency as the exploitation of market power generates automatic benefits, whereas an increase in market power generally comes with a deterioration of efficiency that makes banks unable of earning higher profitability.

In order to solve this debate and methodological problems, Berger and Hannan (1997) suggest to explore the notion of efficiency to explicitly integrate efficiency variables in the equations. In particular, Berger and Mester (1997) summarize the literature on (banking) economic efficiency through the analysis of different efficiency concepts and measurement methods. The different interpretations of efficiency are described next, while the measurement methods are analyzed in subsection 1.3.3.

1.3.2. Different concepts of economic efficiency

In conventional microeconomic theory, firms are assumed to minimize costs irrespective of the market structure or economic environment in which they operate. However, Liebenstein (1975) introduces a theory of the organization of the firm, and its relation to its environment, under which firms do *not* minimize costs (called *X-inefficiency*), and this may hold even under competition. An identical set of inputs at identical prices would lead to a wide variety of outputs under different organizational circumstances. The *X* in X-efficiency would represent an unknown factor responsible for a non-allocative type of inefficiency. Examples for these unexploited opportunities would be lack of motivation, human inertia, and biases in human decision making. They would be a form of inefficiency, but not allocative inefficiency, as they are not related to prices and markets per se; they are related to intra-firm activities and to errors made by individuals inside those firms.

Following this, Berger (1995) divides the efficiency hypothesis into the *X-efficiency* (XE) and *scale-efficiency* (SE) hypotheses. Under the X-efficiency, firms with superior management or production technologies have lower costs and therefore higher profits, which generates larger market shares that may result in higher concentration. The scale-efficiency instead assumes firms have essentially equally good management and technology, but some firms simply produce at more efficient scales than others, therefore having lower unit costs and higher unit profits. Under both interpretations, there is a positive relationship between profit and market structure, but it is efficiency what drives both profits and market structure, being the profit-structure relationship a spurious outcome.

Fiordelisi (2004) focuses instead on three dimensions of the ES hypothesis —namely, production technique, production scale, and resources allocation— to develop three alternative measures: *technical efficiency* —firms that are the best in terms of quantities; *allocative efficiency* —to produce outputs in optimal proportions, given prices and technology; and *scale efficiency*. Finally, Mester (1996) identifies three other levels of efficiency: *scale efficiency* —whether banks are operating with the efficient level of outputs; *scope efficiency* —whether banks are operating with the efficient mix of outputs; and *X-efficiency* —whether banks are using their inputs efficiently.

All these taxonomies, however, refer to a single interpretation of efficiency: cost efficiency. Berger and Mester (1997) two more ones: standard profit and alternative profit efficiencies. In their words, *"these concepts have the best economic foundation for analyzing the efficiency of financial institutions because they are based on economic optimization in reaction to market prices and competition, rather than being based solely on the use of technology"* (p. 898). These efficiency concepts are described next.

Cost efficiency

Cost efficiency is a measure of *how close a bank's cost is to what a best-practice bank's cost would be for producing the same output*. Here the dependent variable is costs, inputs are prices (of deposits, other funds, labor) and outputs are quantities (loans and securities). The cost function is given by[9]

$$C = C(w, y, z, v, u_c, \varepsilon_c) \;\rightarrow\; \ln C = f(w, y, z, v) + \ln u_c + \ln \varepsilon_c\,, \tag{1.1}$$

where C represents variable costs, w input prices, y output quantities, z quantities of fixed netputs (inputs or outputs: e.g. off-balance-sheet items, physical capital, equity capital), v environmental variables (e.g. nonperforming loans over total loans), u_c the inefficiency factor, and ε_c random error.

[9] Equation (1.1) holds assuming inefficiency and random terms u_c and ε_c are multiplicatively separable from the rest of the cost function, and applying natural logs.

The cost efficiency of a bank is expressed as a ratio between the estimated cost needed to produce its output vector if it were as efficient as the best-practice bank in the sample, divided by the actual cost of the bank, and adjusted for random error. The ratio ranges over (0, 1):

$$Cost\,EFF^{\,b} = \frac{C^{\min}}{C^{b}} = \frac{\exp\left[f\left(w^{b}, y^{b}, z^{b}, v^{b}\right)\right]\times\exp\left[\ln u_{C}^{\min}\right]}{\exp\left[f\left(w^{b}, y^{b}, z^{b}, v^{b}\right)\right]\times\exp\left[\ln u_{C}^{b}\right]} = \frac{u_{C}^{\min}}{u_{C}^{b}}\ . \tag{1.2}$$

Then, the studies on bank efficiency are divided into those that examine scale and scope efficiency alone, and those that also examine X-efficiency (Mester, 1996). The first kind of studies estimate an *average practice cost function* which relates bank cost to output levels and input prices, and implicitly assume there is no X-inefficiency and banks are using the same technology. The second kind of studies estimate a *best practice cost function* which represents the predicted cost function of banks that are X-efficient, and then measure the degree of inefficiency of the other banks in the sample. X-efficiency measures would differ in how they distinguish the inefficiency term $ln\ u_c$ from the random error $ln\ \varepsilon_c$.

Standard profit efficiency

The standard profit efficiency is a measure of *how close a bank is to producing the maximum possible profit given a particular level of input and output prices*. Here the dependent variable is profits, inputs are prices (of deposits, other funds, labor) and outputs are prices too (of loans, securities). Other variables (netput, environmental, inefficiency and error term) are included as in the cost function. The function is given by

$$\ln(\pi + \theta) = f(w, p, z, v) + \ln u_{\pi} + \ln \varepsilon_{\pi}\ , \tag{1.3}$$

where π is variable profits (interest and fee income earned on the outputs minus variable costs, C), θ is a constant added to every firm's profit so the natural log is taken of a positive number; p are output prices, u_{π} the inefficiency that reduces profits, and ε_{π} random error.

This definition of profit assumes revenues can be earned by varying both inputs and outputs. The profit efficiency of a bank is also expressed as a ratio, now between predicted actual profits to the predicted maximum profits if it were as efficient as the best-practice bank in the sample —net of random error. The ratio equals 1 for the best-practice bank, but profit efficiency can be negative:

$$Std\ \pi\ EFF^{\,b} = \frac{\pi^{b}}{\pi^{\max}} = \frac{\exp\left[f\left(w^{b}, p^{b}, z^{b}, v^{b}\right)\right]\times\exp\left[\ln u_{C}^{b}\right]-\theta}{\exp\left[f\left(w^{b}, p^{b}, z^{b}, v^{b}\right)\right]\times\exp\left[\ln u_{C}^{\max}\right]-\theta}\ . \tag{1.4}$$

According to Berger and Mester (1997), the profit efficiency is superior to the cost efficiency for evaluating the overall performance of the firm, because the former is based on the more accepted economic goal of profit maximization, which requires the same amount of managerial attention to be paid to raising a marginal dollar of revenue as well as to reducing a marginal dollar of costs. Besides, since cost efficiency evaluates performance setting output constant at its current level, *"standard profit* *efficiency may take better account of cost inefficiency than the cost efficiency measure itself, since standard profit efficiency embodies the cost inefficiency deviations from the optimal point"* (p.900-1).

Alternative profit efficiency

The alternative profit efficiency is a measure of *how close a bank comes to earning maximum profits given its output levels rather than its output prices*. Here, inputs are prices (of deposits, other funds, labor) and outputs are quantities (of loans, securities). That is, the alternative profit function employs the same dependent variable as the standard profit function (profit) but the same exogenous variables as the cost function (input prices, output quantities):

$$\ln(\pi + \theta) = f(w, y, z, v) + \ln u_{a\pi} + \ln \varepsilon_{a\pi} \,, \tag{1.5}$$

where y replaces p in the function f, yielding different values for inefficiency and random error. It is expressed using the same ratio as with standard profit efficiency (see above).

There is no reason to estimate the alternative profit measure under the usual assumptions (Berger and Mester, 1997), but it may provide useful information if one or more of the following conditions hold: substantial unmeasured differences in the quality of banking services; outputs not completely variable (banks cannot achieve every output scale or product mix); output markets not perfectly competitive (banks have market power to charge prices); output prices not accurately measured.

1.3.3. Efficiency measurement methods

After the different efficiency concepts have been described, a question arises: how to measure them? Three concepts become determinant here: (a) the estimation techniques; (b) the functional form (if a parametric technique is chosen); and (c) how to account for risk. We devote the latter to a separate section, while we describe the other two in what follows.

Estimation techniques

Efficiency estimation techniques may be either parametric or non-parametric. Both are largely used in the empirical literature (Berger and Humphrey, 1997) and efficiency estimates are fairly robust to differences in methodology (Berger and Mester, 1997).

Parametric techniques (a.k.a. the econometric approach) correspond well with the cost and profit efficiency concepts described above. A bank is labeled inefficient if its costs are higher or profits are lower than the best-practice bank after removing random error. Different parametric methods differ in the way the inefficiency term *ln u* is disentangled from the composite error *ln u + ln ε* (inefficiency plus random error). The three most common parametric techniques are the stochastic frontier approach (Aigner, Lovell and Schmidt, 1977), the distribution-free approach (Berger, 1993), and the thick frontier approach (Berger and Humphrey, 1991).

First, the stochastic frontier approach makes explicit assumptions about the distributions of *u* and *ε*. On one hand, the error term, *ln ε*, is assumed to be two-sided, usually normally distributed. On the other, the inefficiency term, *ln u*, is assumed to be one-sided, half-normally distributed. The estimated mean of the conditional distribution, $\ln \hat{u} = E(\ln u \mid \ln u + \ln \varepsilon)$, is usually used to measure inefficiency. Second, the distribution-free approach follows Berger (1993), who shows that the assumptions of the stochastic frontier approach are rather arbitrary. These assumptions may be relaxed —if panel data are available— assuming there is an average or *core efficiency* for each firm over time. Then, core inefficiency may be disentangled from *ε* by assuming the former is persistent over time, while random errors tend to average over time. Third, the thick frontier approach divides the sample into four quartiles based on total cost per unit of assets, and assume the estimated cost function for banks in the least average cost quartile is the cost frontier. Banks in the lowest quartile are assumed to be the most efficient, in the highest quartile the least, and differences inside each quartile are assigned to an error term assumed to represent random measurement errors and luck, rather than differences in efficiency (Mester, 1996).

Non-parametric techniques focus on technological optimization (a.k.a. technical efficiency) rather than economic optimization, and do not correspond to the cost and profit efficiency concepts discussed above. These techniques cannot account for allocative inefficiency because they generally ignore prices. Another drawback is that their estimations usually do not allow for a random error —alternatively, they disentangle *ln u* and *ln ε* by setting random error equal to zero.

The most common non-parametric technique is the data envelopment analysis, DEA (Farrell, 1957; Charnes, Cooper and Rhodes, 1978). DEA is a well-established method in the literature that aims to evaluate technical efficiency by defining a frontier envelopment surface for all sample observations. We may distinguish two types of techniques: input-oriented DEA minimizes the inputs necessary to produce a given output set (inputs are endogenous, outputs are exogenous); output-oriented DEA, instead, looks for the maximum outputs achievable given inputs. For instance, the output-oriented efficiency estimator $\hat{\delta}_i$ can be derived by solving the following optimization program (Barros and García-del-Barrio, 2010):

$$\hat{\delta}_i = \max_{\delta,\lambda}\left[\delta > 0 \mid \hat{\delta}_i y_i \leq \sum_{i=1}^{n} y_i \lambda; x_i \geq \sum_{i=1}^{n} x_i \lambda; \lambda \geq 0\right] \tag{1.6}$$

for i = 1,2,...,*n* firms, where y_i is a vector of outputs, x_i a vector of inputs, and λ an I x 1 vector of constants. The linear programming must be solved *n* times, one for each firm. The value obtained for $\hat{\delta}_i$ is the technical efficiency score for the i[th] firm: $\hat{\delta}_i = 1$ implies efficiency and $\hat{\delta}_i > 1$ inefficiency. Charnes et al. (1978) introduced the term DEA to describe the mathematical programming used in the construction of production frontiers and the measurement of efficiency. Their model, known as the CCR model, is probably the best-known and most widely used (Barros and Garcia-del-Barrio, 2010). They assumed constant returns to scale (CRS), while Banker, Charnes and Cooper (1984) (a.k.a. BCC model) were the first to introduce variable returns to scale (VRS). For instance, the model in Eq. (1.6) would be a CRS model, while imposing the constraint $\sum_{i=1}^{n} \lambda = 1$ transforms the model into a VRS one. The CCR model measures the overall efficiency for each firm, aggregating pure technical and scale efficiency into one value. The BCC model, instead, measures pure technical efficiency (managerial skills) alone. This way, using both DEA models we may decompose efficiency into technical and scale efficiencies.[10] Finally, there are at least five other basic DEA models: the multiplicative model (Charnes et al., 1982); the additive model (Charnes et al., 1985); the cone-ratio DEA model (Charnes, 1990); the assurance region DEA model (Thompson et al., 1990); and the super-efficiency model (Andersen and Petersen, 1993).[11]

Other classic non-parametric techniques are the non-parametric Malmquist productivity index (Malmquist, 1953), the free disposable hull analysis (Deprins, Simar and Tulkens, 1984), and the two-stage DEA bootstrapping technique (Simar and Wilson, 2007). They are summarized in what follows. The Malmquist productivity index follows after Malmquist (1953), who proposes a quantity index that uses input distance functions to compare two or more consumption bundles, using an indifference curve of one of the consumers as a reference. Caves, Christensen and Diewert (1982) adapt the index from consumption analysis to production analysis, defining the Malmquist input, output and productivity indexes for general structures of production for two or more firms.

The free disposable hull analysis was first introduced by Deprins et al. (1984). They compare two previous models —one of adjusting a Cobb-Douglas production frontier to data, other of computing the convex hull of the data— to introduce a third method, FDH, *"on the basis of the sole assumptions of input and output disposability"* (p.243). The best feature of FDH is that it relies on the sole assumption that production possibilities satisfy free disposability. Its main drawback, as it was later demonstrated by Thrall (1999), is that it can give a technically efficient classification to output-input vectors that are inefficient in terms of profit maximization. However, some other authors disagree on this conclusion (e.g., Cherchye, Kuosmanen and Post, 1999).

Finally, the DEA bootstrapping technique enhances the original DEA, which is simply to estimate but is criticized for being a non-statistical (deterministic) technique. Developed by Simar and Wilson (2007), the bootstrapping technique allows to benefit from the advantages of DEA, while performing statistical hypothesis testing on the DEA efficiency scores. It consists of a two-stage procedure: in the first stage, a bootstrapped DEA is used to estimate the relative efficiency scores; then, in the second stage, a procedure is implemented to bootstrap the DEA scores with a truncated regression.

---

[10] The scale efficiency score is obtained dividing the aggregate CCR score by the technical efficient BCC score (Fare, Grosskopf and Lovell, 1994). Given the score in the BCC model is at least equal to that in CCR, the maximum scale efficiency score is 1.

[11] Other developments of DEA include disentangling technical and allocative efficiency (Coelli, Rao and Battese, 1998), the directional distance functions and the Luenberger productivity indicator (Luenberger, 1992; Briec, 1997), and the conditional quantile regression (Daouia and Simar, 2007).

Functional form and variables to use

If a parametric model is chosen, a functional form for the cost and profit functions —i.e., $f(w, y, z, v)$ for cost and alternative profit efficiencies, $f(w, p, z, v)$ for standard profit efficiency— must be specified. Two common ones are the translog form and the Fourier-flexible functional form. However popular, the translog form does not necessarily properly fit data that are far from the mean in terms of output size or mix. In consequence, some differences in scale economies may be due to this choice (Berger and Mester, 1997). The Fourier-flexible functional form enhances the translog by including Fourier trigonometric terms, and is a global approximation to virtually any cost or profit function.

A classic dichotomy is about which variables to use. For technical efficiency analysis, for instance in DEA, we must decide the inputs and outputs to be used. Basically, two options are available (Cuadras, Fernández and Rosés, 2002). First, we may think of a bank as a services provider, in such way outputs are both assets —loans, securities, etc.— and liabilities —deposits, current accounts, etc.— whereas inputs are general expenses. Alternatively, we may think of a bank as a financial institution that transforms deposits (inputs) into loans (outputs) and tries to make a profit out of this. Notwithstanding, to test cost and profit efficiencies, other alternatives are available. Berger and Mester (1997) provide a list of variables to be used under their so-called *preferred model* (i.e., what they believe to be *the best set of variables, cost and profit function specification, and frontier efficiency technique* to test cost and profit efficiency). The variables are summarized in Table 1.3.

TABLE 1.3 – Variables in the cost and profit functions by Berger and Mester (1997)

	VARIABLES	DESCRIPTION
DEPENDENT VARIABLES		
Cost	variable operating plus interest costs	includes costs of purchased funds, deposits and labor
Profit	variable profits	includes revenues from loans and securities less variable costs
EXOGENOUS VARIABLES		
Output quantities	consumer loans	including credit cards
	business loans	all other loans
	securities	all non-loan financial assets; ie, gross total assets less (consumer & business loans + physical capital)
Input prices	price of core deposits	
	price of purchased funds	
	price of labor	
Output prices	price of consumer loans	(domestic transactions accounts, time and savings)
	price of business loans	all other liabilities
	price of securities	
Fixed netput quantities	physical capital	
	equity capital	
	off-balance-sheet items	(commitments, letters of credit, derivatives) using Basel Accord risk weights to be risk-equiv. to loans
Environmental variables	ratio of NPL / total loans	NPL = non-performing loans, past due at least 90 days
	weighted aver. NPL for state/province	weighted average using as weight the proportions of the loans issued by banks in the state/province

Source: Berger and Mester (1997), own elaboration

Authors using similar approaches and variables in their tests include, among many others, Bonin, Hasan and Wachtel (2005), Greene (2005), Fries and Taci (2005), Krasnikov, Jayachandran and Kumar

(2009), Koutsomanoli, Margaritis and Staikouras (2009), Karas, Schoors and Weill (2010) and Lozano-Vivas and Pasiouras (2010). Hence, for the purposes of our research in Part III, we will use this list of variables as representative of the banking efficiency literature.

1.3.4. The problem with risk in efficiency tests of financial institutions

Risk affects banks in several instances. Indeed, the key role of financial institutions is to manage, monitor and/or trade with risk. The different techniques described, as well as the different efficiency concepts used, would be of little value if they did not account for the risk incurred by the firms in their strategic decisions. In particular, three ways risk could be incorporated to the analysis of banking efficiency are output quality, financial capital and risk preferences.

Output quality

Banks produce services of a highly heterogeneous quality. For instance, commercial loans can vary in size, repayment schedule, risk, transparency of information, type of collateral, covenants to be enforced, etc. When one bank is compared to other in terms of (cost or profit) efficiency, the comparison should be between banks producing the *same output quality* (Berger and Mester, 1997). Otherwise, bad management and excessive lending might be disguised as an apparently highly efficient bank. In Mester (1996)'s words: *"unless quality and risk are controlled for, one might easily miscalculate a bank's level of inefficiency: banks skimping on credit evaluations or producing excessively risky loans might be labeled as efficient when compared to banks spending resources to ensure their loans are of higher quality"* (p.1026).

The effect of output quality is twofold. On one hand, differences in quality are likely to affect the costs to the bank of loan origination, monitoring and control, and financing expense. Hence, managers might be tempted to cut back on those expenses (known as *skimping*). On the other, as a consequence of skimping or of bad management (e.g., managers' excessive risk-seeking), banks could be granting high-risk loans with low delinquency ratios today, but which years ahead, under worsen economic conditions, might make the ratio of non-performing loans to total loans soar. Berger and DeYoung (1997) test these bad luck, bad management and skimping hypotheses, to find mixed evidence.[12]

Two ways to control for output quality in parametric models are in order. One is to use the alternative profit measure which, as already discussed, helps to control for unmeasured differences in output quality. The other is to include environmental variables in the model —denoted v in equations (1.1), (1.3) and (1.5) above. Examples of these type of variables are the volume of nonperforming loans (Hughes and Mester, 1993; Mester, 1996), loan losses (Berg, Forsund and James, 1992) and the ratio of nonperforming loans to total loans (Berger and Mester, 1997).

[12] They find evidence in both senses: problem loans precede reductions in measured cost efficiency and cost efficiency precedes reductions in problem loans. They also find that reductions in capital at thinly capitalized banks precede increases in problem loans. Berger and DeYoung (1997) claim cost efficiency may be an important indicator of future problem loans and problem banks, but results are ambiguous concerning whether researchers should control for problem loans in efficiency estimation.

Financial capital

A bank's insolvency risk depends not only on the quality of its assets, but on the financial capital (equity) available to absorb potential portfolio losses. Since these insolvency risks affect bank costs and profits through a higher risk premium to be paid for uninsured debt, one way to measure and take into account insolvency risk in the models above is to control for the interest rates paid on uninsured debt. However, these rates are imperfectly measured (Berger and Mester, 1997).

Mester (1996) solves it using equity as an input into the production process. Financial capital provides a cushion against losses, and represents an alternative to deposits as a funding source for loans, with its pros and cons: interests paid on debt count as a cost while dividends paid do not, but raising equity typically involves higher costs. In any way, a failure to control for equity could yield a scale bias —because large banks tend to depend more on debt financing than small banks. Omitting capital level and price would make sense only if it is assumed that financial capital is not used to fund loans, or its price is the same across all banks *and* banks use the cost-minimizing level of financial capital —none of which seems plausible (Mester, 1996). Besides, cost-minimization does not fully explain a bank's capital level when there are, for instance, regulations that set minimum capitalization ratios.

Risk preferences

Finally, there is another reason why we should control for equity in banking efficiency measures: risk preferences. The cost, standard profit and alternative profit efficiency concepts **take as given that banks are risk neutral**. Risk averse banks may hold a higher level of financial capital than the level that maximizes profits or minimizes costs. Indeed, Hughes and Moon (1995) tested and rejected the assumption of risk neutrality for banks, so if financial capital is ignored, the efficiency of risk-averse banks would be miss-measured, even though they behave optimally given their risk preferences.

1.4. THEORIES OF CREDIT

The discussion in Section 1.3 about the necessity to control for risk and asset quality in banking efficiency analysis leads us to another relevant field in the literature: the different theories that interpret how banks provide credit to the economy. In what follows we make a short review of this literature.

1.4.1. Microeconomics of credit

A review on what determines how much private credit a bank would extend to firms and individuals is offered by Djankov, McLiesh and Shleifer (2005), who distinguish two broad views.[13] First, what matters

[13] Alternatively, Diamond (1984) considers financial intermediation may be related to either the agent–principal literature, which develops conditions when monitoring additional information about an agent will help resolve moral hazard problems, or the literature on imperfect information, about the gross benefits of delegating some informational task to an intermediary.

for the viability of private credit is the power of creditors (Townsend, 1979; Aghion and Bolton, 1992; Hart and Moore, 1994, 1998). These *power theories of credit* consider banks are more willing to extend credit the more easily they can force repayment, grab collateral, or even gain control of the firm. The second alternative is *information theories*: what matters for lending is information (Jaffe and Russell, 1976; Stiglitz and Weiss, 1981). The more banks know about their clients (their credit history, financial situation, etc.), the more credit they are willing to extend since information reduces the *lemons* problem (Akerlof, 1970).

Townsend (1979) represents the starting point for the power theories of credit. Arrow (1964) and Debreu (1959) suggest uncertainty is easy to incorporate into general equilibrium models *à la* Arrow and Debreu (1954). However, Townsend (1979) notices it is not common that agents agree to contract contingent dealings that depend on the state of nature. This observed absence of contingent dealings would be related to moral hazard and imperfect information (Arrow, 1974): the range of possible contingent contracts is limited to those which are easily verified by both parties. In addition, the information structure of an economy may be costly and endogenous (Radner, 1968). Townsend works on these themes suggested by Arrow and Radner to provide a model where information may be transmitted to other agents only if a verification cost is borne. The incentive compatibility of alternative contracts is then discussed.

Following this recognition that financial contracts are inherently incomplete, a theory of vertical integration of companies followed in consequence (e.g., Grossman and Hart, 1986). Aghion and Bolton (1992) develop instead a theory of capital structure based on control rights. They work on the alternative situation where firms face wealth constraints —hence vertical integration is not feasible— to provide a theory on the classic corporate finance decision to use debt or equity to finance their activities. The optimality properties of debt depend on the ability to implement two forms of efficient control allocation: (i) unilateral control allocations, where the entrepreneur or the investor are the sole owners of the firm; and (ii) contingent allocations of control, where the entrepreneur retains control of the firm only if he does not default on his debt obligations —otherwise the investor gets the control rights.

Finally, Hart and Moore extend the analysis in two instances. Hart and Moore (1994) analyze the case where the entrepreneur has some special skills, which implies his human capital cannot costlessly be replaced. They show that the threat of repudiation (the entrepreneur withdrawing his human capital) implies some profitable projects will not be financed. Hart and Moore (1998) discuss the trade-off between the size of the loan and the repayment for a debt contract to be optimal —that is, to persuade an entrepreneur to pay out cash flows rather than to divert them.

Informational theories base their analysis instead in confronting the ability of borrowers to repay their debts on one hand (which basically depends on the expected future income of their assets and the collateral pledged), and the ability of lenders to screen good borrowers from bad ones to implement the credit policies that maximize their profits adjusted by risk, on the other. Two classic articles are Jaffe and Russell (1976) and Stiglitz and Weiss (1981). The former analyzes the rationale of credit rationing —that is, when lenders quote an interest rate on loans and then supply a smaller loan size than that demanded by the borrowers. Jaffe and Russell (1976) develop a model where, in a context of imperfect information and uncertainty, credit rationing arises as a market response to adverse selection.[14] Stiglitz and Weiss (1981) show that under imperfect information the interest rate acts either as a screening device or as an incentive mechanism, so a loan market in equilibrium may be characterized by credit rationing. An increase in the interest rate charged borrowers will, in general, increase the average riskiness of the projects a bank is financing (Greenwald, Stiglitz and Weiss, 1985).

Literature on business failure

A classic field inside information theories is the literature on business failure. It is one of the most investigated topics in the business literature (Balcaen and Ooghe, 2006) that starts with the classic articles by Beaver (1966) and Altman (1968). A business failure and its possible dissolution may affect not only to the stakeholders of the firm, but to its workers, customers, suppliers, and creditors. In consequence, the business failure prediction literature, also known as literature on default and credit risk modelling (Carling et al., 2007) develops statistical methods to determine a firm's bankruptcy risk as accurately as possible (Crutzen and Van Caillie, 2008).

In these methods, financial statement analysis often plays a key role. The causes of a business failure (Argenti, 1976) may be internal (e.g., declining sales, loss of market share, poor management, loss of competitiveness, high indebtedness, unprofitable investments) or external (e.g., GDP growth, economic, technological progress, social and political changes...). Whatever the cause, they are manifested as a series of symptoms that are observable in the financial statements of the firm, such as low profitability, low productivity, liquidity problems, difficulties getting access to financing sources, higher delinquency ratios, etc. Consequently, the ability of banks to properly discriminate good borrowers from bad ones largely depends on the analysis of accounting information, basically by making use of financial ratios that analyze both the situation (balance sheet) and cash flows (income statement) of the company.

A basic taxonomy (Rodríguez, 2000) on methods of business failure prediction splits them into univariate and multivariate (either opinion-based, parametric or non-parametric). Univariate models consider financial ratios one to one, and try to determine their tendency and ability to predict the failure. Multivariate models try the same by analyzing a series of independent variables, including financial ratios, cash flow analysis, and macroeconomic data. The first stage in the development of multivariate

[14] In particular, Jaffe and Russell (1976) make two specific assumptions. First, there are "honest" and "dishonest" borrowers: honest borrowers accept only loan contracts that they expect to repay and they do in fact repay them; dishonest people instead default on loans whenever the costs of default are sufficiently low. Second, lenders are unable to distinguish between the two types of individuals on an a priori basis, who can only be identified by actual defaults.

analysis were the opinion-based models (Wall and Dunning, 1928; Tamari, 1966; Argenti, 1984) which basically consisted of synthesizing a set of ratios in a single indicator. Parametric models are divided into descriptive (factorial analysis, cluster analysis, etc.) and predictive methods (multiple linear regression, discriminant models, conditional probability models, etc. Finally, non-parametric models include DEA and heuristic models, among others (Rodriguez, 2000). Most of them make use of financial ratios in their analysis. A list of ratios claimed to have better predictive power according to the empirical literature would include: return (ROA, ROE, return on sales); solvency; liquidity (quick ratio, acid test); efficiency (productivity per employee, commercial margin); indebtedness (leverage ratios); structure ratios; rotation ratios; market ratios (PER, P/CF).[15]

1.4.2. Macroeconomics of credit. Bubbles

Power and informational theories of credit study how banks analyze the appropriateness of granting credit at the individual level. However, what happens when banks compete among them? How does the industry behave when granting credit to the economy? This is, indeed, a key question for the purpose of this thesis.

Some theories explain why credit markets may malfunction. These include the financial instability hypothesis (Minsky, 1982a,b; 1992) and the related concept of the Post Keynesian endogenous money model (Moore, 1988), the literature on imperfect information (Stiglitz and Weiss 1981, 1983; Greenwald et al. 1985), the role of incentives and risk taking moral hazard (Fahlenbrach and Stulz, 2011; Acharya and Naqvi, 2012) and the literature on credit bubbles that starts with Kindleberger (1978). We describe these theories below, but for now let us say a point in common among them is that they all stress the key role *volume* plays in the price mechanism of credit markets. In stock markets, the volume of securities potentially available —i.e., the number of shares of a stock that could be offered— is constant or at least rather *sticky* in the short term. This yields two differences between financial and credit markets. On one hand, markets clear by setting the price that balances supply and demand at any level. Credit markets, instead, might not clear (Stiglitz, 1993). On the other, potential supply in stock markets may be increased through a share offer, for instance, but that does not happen all the time. In retail credit markets, instead, banks may boost credit supply by simply easing their credit policies.

Minsky (1982a,b) stresses the relationship between volumes of debt accumulated by the private sector, and the debt payments (interests and principal) associated to them, compared to the income generated from the investments that debt finances. Minsky's financial instability hypothesis, FIH, is a theory of financially driven business cycles which can lead to an eventual debt-deflationary crisis. In short, it asserts stability is destabilizing: the second theorem of the FIH postulates that, over periods of

[15] The list is based on a review of an extensive number of empirical research papers, including Beaver (1966), Lev (1978), Laffarga, Martín and Vázquez (1985), Courtis (1987), Mora (1994), Laffarga and Mora (2002), Calvo-Flores and García Pérez (2002), and Rodríguez (2002).

prolonged prosperity, the economy naturally transits from hedge finance —the only income-debt relationship that ensures equilibrium in the economy— to speculative and Ponzi finance.[16] Minsky sees bankers as *merchants of debt* trying to profit out of it. At the beginning of the economic expansion, banks and firms act conservatively due to risk aversion caused by a memory of a not too distant financial failure. Then, the good economic performance makes bankers and managers perceive risk premiums are excessive and that *it pays to lever*. Higher leverage leads to a euphoric economy and, eventually, to speculative and Ponzi schemes that cause debt deflation and economic turmoil (Keen, 2011).

Minsky's interpretation of business cycles being driven by credit is related to the Post Keynesian endogenous money model (Moore, 1988). In the era of modern liability management, bank lending operations are neither deposit nor reserve constrained: instead, loans make deposits and deposits make reserves (Lavoie, 1984). Recent research evidences banking credit booms are related to the business cycle. Jorda, Schularick and Taylor (2011) show higher rates of credit growth relative to GDP tend to be followed by deeper recessions and slower recoveries. Carpenter and Demiralp (2010) note the money multiplier is not useful to assess the effects of monetary policy on future money growth or bank lending.

Upswings, when based on credit booms, are often induced by financial innovations (Brown, 1997). The development of financial innovations such as the collateralized debt obligations (CDO) or the credit default swaps (CDS) surely would have made the consequences of overconfidence over leverage more severe, also fostering demand-side effects (Brown, 2007). Under the money endogeneity principle, the supply of reserves is horizontal at the central bank's target and, since they pay low or even zero rates, banks continually innovate to reduce the quantity of reserves they need to hold, increasing the rate of return on equity within regulatory constraints (Wray, 2007). This was evident for Alan Greenspan himself, who complained how easy it was for CEOs to craft financial statements to deceive the public (Friedman and Friedman, 2009). Boz and Mendoza (2014) provide a model of financial innovation and overconfidence in the context of the U.S. credit crisis, showing that financial innovation can lead to significant underestimation of risk.

A second branch of theories that explain why credit markets could malfunction is the literature on imperfect information, which highlights the externalities of financial disruption and the Pareto inefficiency of credit markets. Following Stiglitz (1993), standard theories require perfect information, but information is a public good: because of the difficulties in appropriating the returns of information, there are externalities associated with its acquisition. Thus, information-intensive markets are hence likely to be imperfectly competitive.

[16] Hedge financing agents are able to meet all their financial obligations with the cash flows generated by the assets they own. Speculative finance units can pay the interest on their debt, but need to 'roll over' their liabilities as they expire. Finally, for Ponzi subjects, the cash flows from operations are not enough to meet either the principal or the interest on their debt, so they are forced to increase their indebtedness, or sell assets to meet the payments required.

The main informational problem banks face is that they do not know how the money they lend is being invested (Greenwald et al., 1985). This yields two results. First, credit markets cannot operate like ordinary auction markets, with the funds going to the highest bidder; hence, with imperfect information, markets may not clear. Stiglitz and Weiss (1981, 1983) show that an increase in the interest rate charged on borrowers will, in general, increase the average riskiness of the projects a bank is financing.[17] A higher risk may outweigh the direct gain to the bank from increasing the interest rate, hence the bank's profit may be maximized at an interest rate at which there is an excess demand for loanable funds. Credit rationing appears when, at this profit-maximizing interest rate, there exists excess demand for credit (Stiglitz, 1993). The second result comes in consequence. Greenwald and Stiglitz (1986) show that, when information is endogenous or markets incomplete, the economy is not constrained Pareto optimal. Hence, there may be government interventions that take into account the costs of information and of establishing markets that can make all individuals better off. [18]

A third, more recent line of investigation on the macroeconomics of credit is about the effects that incentives to CEOs had on excessive lending by banks —perhaps inspired by the recent financial crisis. The basic argument would be that executives at banks had poor incentives because their compensation was not properly related to long-term performance. However, Fahlenbrach and Stulz (2011) find some evidence that banks with CEOs whose incentives were better aligned with the interests of shareholders performed worse and no evidence that they performed better. Contrariwise, Acharya and Naqvi (2012) develop a theoretical model where abundant liquidity —defined as deposits received from investors— aggravates the risk-taking moral hazard at banks. In their model, incentives paid to loan officers based on the volume of loans granted induces greater risk taking. They show bank liquidity is likely to increase when the macroeconomic risk is high and investors switch from direct investments to savings in the form of bank deposits. Abundant liquidity aggravates the risk-taking moral hazard by CEOs at banks, who relax lending standards giving rise to excessive lending and asset price bubbles.

However, if a theory on why credit markets may malfunction should be mention that is the work of Charles Kindleberger, on which most literature on credit bubbles sets its background. Kindleberger (1978) provides an *anatomy of a price bubble*: a self-sustaining disequilibrating process that starts with some good news that generate a profit in an asset, followed by a *smart-money response* where both supply and demand are encouraged by initial investors. The bubble is sustained by the same investors who stimulate positive feedback trading by facilitating noise trader speculation. That is, the same agents

[17] This may happen either because borrowers switch to riskier projects or because investors with safer projects do not apply for loans as their projects become relatively less attractive (Greenwald et al., 1985).

[18] Following Greenwald et al. (1985), credit rationing would help to explain business cycles in three ways. First, by providing a rationale for the persistence of non-market-clearing. Second, a firm's cost of capital may vary unrelated to observed variations in interest rates. Credit rationing in recessions may be persistent, both because greater uncertainty concerning the prospects of the firms and an increase in the dead-weight loss associated with bankruptcy. Third, stabilization policy is likely to work if it focuses on increasing the availability of loanable funds to increase investment, rather than focusing on lowering interest rates —which would not work as there is no shortage of willing borrowers.

who are benefited in the early stages of the bubble increase the asset supply and encourage other actors to participate, increasing the demand and sustaining asset prices until the market, eventually, collapses.

Thus, bubbles in financial markets require supply to be encouraged as the price goes up. However, as we mentioned, this effect on supply is easier to be observed in retail credit markets, since banks may easily boost credit supply by simply easing their credit policies. Hence, a key feature in Kindleberger (1978)'s theory is the role credit always plays in asset bubbles: *"You can't have a real estate bubble without the rapid growth of credit"* (p.62). Therefore, we devote a separate section to provide a review on the theory of bubbles beyond Kindleberger, to conclude Chapter 1.

Bubbles

Shleifer (2000) defines a price bubble as a situation in which *"prices go up and up without much news just because noise traders are chasing the trend. Noise traders in price bubbles react to past price changes, as opposed to particular news"* (p.154). In such situation, a bubble is a deviation of the market price from the asset's fundamental value (Scherbina, 2013). A common feature of asset bubbles is the coexistence of high prices, high trading volume and high price volatility (Cochrane, 2002). A classic explanation of how bubbles may appear is speculation (Harrison and Kreps, 1978), defined as investors buying assets at prices that exceed their own valuations because they think they will be able to sell them later even higher.

There is large evidence of the existence of asset bubbles, both empirically and experimentally. Price bubbles often precede financial crises. Historic examples are the Dutch Tulip mania, the South Sea bubble in England, the Mississippi bubble in France and the Great Crash of 1929 in the United States. Examples in the recent decades are manifold: the collapse of real estate and stock prices in Japan in 1990; Norway, Finland and Sweden in the 1980's and early 1990's; and several financial crises in emerging economies like Argentina, Chile, Indonesia, Mexico, and the South East Asian economies (Allen and Gale, 2000). The recent global financial crisis of 2008 was not, therefore, an exception.

Experimental research has also provided extensive evidence of the existence of bubbles. Smith, Suchanek and Williams (1988) study asset trading in an environment where all investors receive the same dividend from a known probability distribution. The results show fourteen of twenty-two experiments exhibit price bubbles —i.e., prices well-above known fundamentals- followed by crashes. Experienced traders reduce, but not eliminate, the probability of a bubble. Subsequent research traces market features that would reduce the impact and frequency of bubbles. Porter and Smith (1995), for instance, extend the analysis by Smith et al. (1988) introducing a futures market that provides market participants with information on the later period price expectations. Their results evidence that the futures market reduced the bubble. Furthermore, Dufwenberg, Lindqvist and Moore (2005) repeat the setup by Smith et al. (1988) but introducing a small subset of traders that were more experienced in the sense that they had previously participated in three rounds of the game. They find bubbles are substantially reduced or eliminated, and suggest that bubbles in real markets, where the fraction of experienced traders is greater and they are substantially more experienced, would only be episodes that happen once in a while.

Kindleberger's anatomy of a price bubble represents a classic interpretation of how these bubbles occur. For instance, Hens and Bachmann (2008) use it to explain the financial crisis of 2008 based on the role played by subprime mortgages.[19] Akerlof and Shiller (2009a) agree with Kindleberger in the sense that investors buying or selling in reaction to stock price increases or decreases can feed back into additional price changes in the same direction. Though this price-to-price feedback may not suffice to create a major asset bubble, they say, other forms of feedback between asset prices and the real economy could reinforce it. Three sources for this would be a wealth effect, that asset prices also determine investment levels, and that leverage intensify other kinds of feedback effects. Unfortunately, when asset prices fall the feedback process works in reverse. Akerlof and Shiller note the leverage cycle operates in part because of bank capital requirements: rising asset prices increase banks' capital above regulatory requirements, hence they may buy more assets, bidding prices up and freeing more capital... However, when asset prices fall, leveraged financial institutions have to meet their capital requirements by selling. If this effect become systemic, downward feedback fosters fire sales, collapsing prices.

The theory of speculative bubbles flourished after Shiller (1981)'s empirical evidence of an excessive price volatility. Indeed, bubbles represent a challenge to standard asset pricing theories. A successful theory should explain why rational and informed agents optimally choose to hold bubbles in their portfolios, and characterize the macroeconomic consequences of their choice. Behavioral finance, instead, departs from the assumption of rationality to suggest that the presence of psychological biases of market participants suffices to generate a bubble. Scherbina (2013) classifies these behavioral models that explain asset bubbles in four categories: differences of opinion and short sale constraints; feedback trading; biased self-attribution; and the representativeness heuristic and conservatism.

First, models on differences of opinion show that optimism and overconfidence, among other sources of investor disagreement, may foster bubbles. This scope is similar to that we will follow in the theoretical model in Chapter 9. A classic example of this literature is the model by Scheinkman and Xiong (2003), who use a similar approach to that by Harrison and Kreps (1978) where agents agree to disagree and short selling is not possible. The model is based on overconfidence, what generates different opinions about asset fundamentals: an investor could buy an asset and an American option to sell it to

[19] According to them, the initial good news that raised prices on the real estate market would be the speculative money coming into the house market after the dot-com bubble burst. That was followed by a response by the smart-money investors who started the packaging of mortgage risks in new securities (MBS) that are sold outsourced in special investment vehicles (SIV) and sold worldwide.

other agents with more optimistic beliefs. This would foster a bubble in asset prices when small differences of beliefs are sufficient to generate a trade.

Second, models of feedback trading assume a group of investors trade based on past price movements. This interpretation is closer to that by Kindleberger (1978), and is followed by Shiller (2002), who argues mass media amplify feedback trading tendencies, and DeLong et al. (1990b), who combine momentum traders and rational traders in their model to show that rational speculators, rather than arbitrage the market, will trade with the mispricing to sell at inflated prices tomorrow. Third, models based on biased self-attribution consider investors that only recognize those events that confirm their beliefs while those that contradict them are dismissed or attributed to external noise or sabotage. A classic model would be Daniel, Hirshleifer and Subrahmanyam (1998). Fourth, models on the representativeness heuristic and the conservatism bias combine these two deviations from optimal Bayesian updating largely documented in psychology (Tversky and Kahneman, 1982b; and Edwards, 1968, respectively). Representativeness would explain overreaction while conservatism would explain underreaction. A classic model of this type would be Barberis, Shleifer and Vishny (1998).

There is, however, an alternative view that suggest the possibility of bubbles to be rational —known as the *rational bubble* literature. Shiller and Summers on one side, and Fama on the other, started the debate between rational and irrational bubbles. Shiller and Summers on one hand present evidence that stock prices could take large slowly decaying swings away from fundamental values, due to fads or irrational bubbles (Fama, 1991). This implies markets would be inefficient but in a way that is missed in tests on short horizon returns, because they show no autocorrelation. Fama and French (1988a) on the other obtain similar results, but they emphasize that temporary swings in stock prices do not necessarily imply irrational bubbles as in the Shiller-Summers model: a slowly mean-reverting component of stock prices tends to induce negative autocorrelation in returns for long periods, but weak autocorrelation for daily or weekly holding periods. Fama (1991) puts it in short: irrational bubbles in stock prices are indistinguishable from rational time-varying expected returns.

The seminal papers of the rational bubble literature by Tirole (1982, 1985) interpret bubbles as a remedy to the problem of dynamic inefficiency. Tirole (1982) analyzes static and dynamic speculation when traders have rational expectations, to conclude price bubbles rely on the myopia of traders and they disappear if they adopt a dynamic maximizing behavior. Tirole (1985) identifies Samuelson (1958) as the paper that uncovered dynamic inefficiency, and its consumption loan model to be the first that shows a bubble on money can rationally exist. Their argument is based on the dual role of capital as a productive asset and a store of value: money has a positive value despite its market fundamental is zero. Thus, a bubble —defined as the difference between price and fundamentals— appears. Tirole (1985) investigates an overlapping generations model with capital accumulation to give necessary and sufficient conditions for the existence of an aggregate bubble on assets that are held for more speculative purposes than money. Rational models conclude that when all agents are perfectly rational and all information is common knowledge, bubbles can exist for an infinitely-lived asset if the bubble's rate of growth is equal to the discount rate (Scherbina, 2013). Abel et al. (1989) develop a criterion for determining whether an economy is dynamically efficient and conclude that the economies of major OECD countries are so.

The experimental research by Smith et al. (1988) *et seq.* provides evidence against this interpretation, as the bubbles observed in the experiments are without question market inefficiencies: participants were given everything they needed to calculate fundamentals, but in most experiments prices rose way above the fundamental value, only to crash at the end. Notwithstanding, Smith et al.'s results also qualify the rational bubble interpretation to some extent. According to them, when the lagged excess bids observed in the experimental market go to zero, results converge to rational expectations in the sense of unprofitable arbitrage (Fama, 1970). They also subscribe to Tirole (1982)'s view that bubbles might be a form of temporary myopia: agents would learn that capital gains expectations are only temporary sustainable, ultimately inducing common expectations. In any case, rational expectations would require an experiential process through which participants come to have common expectations (Porter and Smith, 1995). Finally, some recent experimental research suggest bubbles may simply do not appear. Two examples are Lei and Vesely (2009), who introduce a pre-market phase in which subjects observe and receive a dividend flow to find that the bubble-and-crash phenomenon never occurs in the experiment, and Kirchler, Huber and Stockl (2011), who observe that the declining fundamental value process assumed by Smith et al. (1988) confuses subjects: running the experiment with a different fundamental value process reduces mispricing as it reduces confusion.[20]

Whether bubbles are rational or not is, eventually, a debate on asset-pricing models and attitudes toward risk. Since CAPM and other asset-pricing models of standard finance measure differences in expected returns of securities at a given point in time, testing whether stock markets may experience bubbles requires analyzing expected returns over time, and whether risk premiums change over time or not (Statman, 1999). The efficient market hypothesis, EMH (Fama, 1970) claims security prices are rational, meaning they reflect only fundamental characteristics —such as risk— but not psychological ones —such as sentiment (Statman, 1999). Behavioral finance claims instead that, beyond attitudes toward risk, risk premiums may be affected by psychological issues. Shefrin (1999), for instance, shows theoretically and empirically that both fundamentals and sentiment affect the risk premium. The debate between rationalists and behaviorists also extends to the rationalist critique of behavioral models in the

[20] Recent papers subscribing to the rational approach are Caballero and Krishnamurthy (2006), who argue bubbles would be a useful source of liquidity in emerging market economies, Kraay and Ventura (2007), who provide a formal description of how bubbles and debt interact as they compete for a fixed pool of savings, Kocherlakota (2009), who constructs a model in which a stochastic bubble in the price of collateral allows entrepreneurs to reallocate capital more efficiently, Martin and Ventura (2011a,b), who interpret that the market for bubbles and the credit market are two natural channels through which bubbles may transfer resources from inefficient to efficient investments, and Farhi and Tirole (2012), who find bubbles are more likely to appear the scarcer the supply of outside liquidity.

sense that, even if sentiment affects prices, arbitrage forces should eliminate all mispricing. The literature of limits of arbitrage (see Chapter 3) by Shleifer and Vishny (1997), DeLong et al. (1990b) and Abreu and Brunnermeier (2003), among others, would come to respond that critique. Consequently, the purpose of the subsequent chapters is to delve into this debate between rationalists and behaviorists, in particular when it refers to the efficiency of financial markets.

1.5. CONCLUDING REMARKS

The way efficiency is interpreted in financial markets —which will be described in detail in Chapter 2— differs to how it is often analyzed in the context of banking competition. In the classic paradigm of banking theory, the role of market microstructure and the effects of asymmetries of information are determinant. Thus, in this chapter we have focused on identifying the classic approaches in the literature to analyze the efficiency of the banking sector when providing credit to the economy. In what follows we summarize the main topics discussed.

First, we have delimited the scope of our analysis, which is bank-based financial systems and, in particular, retail credit markets —that is, the transactions between retail banks and their customers that involve some sort of credit granted such as loans, mortgages, other credit instruments.

Second, we have provided a short review of the literature on banking efficiency. For such purpose, we have confronted the efficient structure and market power hypotheses in the interpretation of whether it is an oligopolistic bank structure what determines performance or, alternatively, it is efficiency what determines both the market structure and the performance of the firms. We ended this review with an enumeration of the different interpretations of efficiency, measurement methods, and relevant variables used in these models to determine the efficiency of the banking sector.

Third, we reviewed as well the different theories that interpret what determines how much credit banks should grant and to whom. We firstly analyzed the microeconomics of credit: that is, some alternative theories on what determines whether banks grant credit to a potential borrower. Then, some additional insights were provided to justify how retail credit markets may malfunction, including the literature on credit bubbles that starts with Kindleberger (1978).

Now, the purpose of this thesis will be to extend the alternatives to analyze the efficiency of retail credit markets. Thus, in the subsequent chapters we will discuss how the way behavioral finance (see Chapter 3) has challenged the tenets of market efficiency (see Chapter 2) in financial markets might be applied to analyze the efficiency of bank-based systems as well.

CHAPTER 2. EFFICIENCY IN FINANCIAL MARKETS: THE EFFICIENT MARKET HYPOTHESIS

2.1. INTRODUCTION. EFFICIENCY IN FINANCIAL MARKETS

The debate about efficiency of financial markets has been —and continues to be— among the most bitter and extensive debates in Finance. Lo and MacKinlay (2001), for instance, in their best-seller *A non-random walk down Wall Street*, declare the Efficient Market Hypothesis (EMH) *"one of the most controversial and well-studied propositions in all the social sciences. It is disarmingly simple to state, has far-reaching consequences for academic pursuits and business practice, and yet is surprisingly resilient to empirical proof or refutation. Even after three decades of research and literally thousands of journal articles, economists have not yet reached a consensus about whether markets —particularly financial markets— are efficient or not"* (p. 6). Indeed, stock market prices have probably been the most analyzed economic data during the last decades (Granger, 1992).

Historically, during the first half of the 20th century, the orthodoxy about how financial markets work and assets are priced were dominated by fundamental analysis —e.g., Wall and Dunning (1928)— and technical analysis —the theories of Dow and Elliot on stock market cycles. The prevailing belief was that a profound analysis of the financial statements of companies and the history of market cycles would allow savvier researchers to earn windfall profits by taking advantage of mispricing generated by irrational markets driven by investors' greed and fears. Then, Kendall (1953)'s empirical analysis came to support the contrarian hypothesis that market prices are random —a *random walk hypothesis* that had, nonetheless, an antecedent in Bachelier (1900).

The random walk hypothesis represented a first step to the EMH that Fama (1970) would propose years ahead, but it also meant a first step into a new era of finance. In the following two decades, several studies on portfolio theory (Markowitz, 1952), arbitrage principles and capital structure (Modigliani and Miller, 1958), asset pricing theory (Sharpe 1963, 1964; Lintner, 1965), market efficiency (Samuelson, 1965; Fama, 1965a, 1970) and option pricing theory (Black and Scholes, 1973; Merton, 1973a) set the pillars of modern standard finance. Since then, markets were seen as essentially efficient, being inefficiencies (*anomalies*) the exception or caused by malfunctioning markets (Malkiel, 2003). Market efficiency became orthodoxy since the 70s; nonetheless, a large number of financial researchers have focused on providing evidence that challenges it, too. This way, market efficiency became the controversial and well-studied area of finance we mentioned… but, why? Why has the efficiency of financial markets become such a popular topic among academics? One might anticipate that efficiency is a fundamental requirement for a well-functioning market, but this argument deserves further insight.

Financial markets play an essential role in capitalist economies because of the wide range of functions they are assigned. First, they facilitate the raising and flowing of capital within the economy, linking agents willing to save to agents willing to borrow capital to invest. Second, they improve the liquidity of the economy and reduce liquidity risk by reducing information costs, providing a means to cash out investments in shorter periods of time and facilitating intermediation (search of counterparty). Third, they facilitate to transfer risks between agents willing to hedge them and agents willing to take them. Fourth, financial markets enhance the three basic characteristics of financial securities —liquidity, risk and return— in a way any investor could elaborate a portfolio that best suits her investment necessities and risk-return profile.

However, above all, *"the primary role of financial markets is allocation of ownership of the economy's capital stock"* (Fama, 1970, p. 383). That is, prices are key to solve the fundamental economic problem: the allocation of scarce means that have alternative ends (Robbins, 1935). Such role requires a pricing mechanism that provides the information necessary for firms to make production and investment decisions, and for investors willing to finance them, with prices that reflect their 'true value'. This way, capital flows according to its price and corresponding discount factors. Financial markets crucial role is pricing securities (capital resources), and whether market efficiency is satisfied requires the analysis of whether this objective is achieved or not.

Chapter 2 is intended to summarize the topics discussed in the last decades about financial market efficiency. This way, the remainder of the chapter is organized as follows. Section 2.2 provides an extensive insight on the theoretical foundations of market efficiency, EMH. Section 2.3 discusses on the testability of EMH, introducing several ways academics have criticized the refutability of EMH. Section 2.4 summarizes the different approaches suggested to test the efficient market hypothesis and the most relevant results that were obtained. Finally, Section 2.5 provides some concluding remarks.

2.2. THEORETICAL FOUNDATIONS OF MARKET EFFICIENCY

We saw in Chapter 1 that a common classification separates bank-based and market-based financial systems. In market-based systems, firms expect financial markets to meet their needs. Financial markets are the place or mechanism where securities, commodities and other assets are traded to set their prices in accordance to supply and demand. Since they play a relevant role in capitalist economies, a classic requirement for financial markets is their efficiency. The word efficiency applied to financial markets often evokes misleading meanings to an ignorant of the art, such as the idea that it requires markets to be perfect or infallible —in the sense that they are able to predict the future. However, financial market efficiency does not mean markets are perfect. A perfect market in the sense of an Arrow-Debreu competitive economy (Arrow and Debrew, 1954) is a fully competitive and frictionless market that provides market participants with complete and homogeneous information about the items traded there.[21] Real-world markets are not that perfect, but efficiency conditions are much less restrictive. Financial market efficiency neither assumes markets are infallible. Efficiency, we will see, does not imply an ability to predict prices: it just presumes prices fully reflect information available.

2.2.1. Financial market efficiency: A definition

A financial market is said to be perfectly efficient if it is simultaneously allocatively, operationally and informationally efficient (Blake, 2000). First, it would be allocatively efficient if it distributes scarce resources between competing aims the most productive way, setting prices such that the highest bidder for the resources gets to use them. Following Bouchaud, Farmer and Lillo (2008), allocative efficiency strictly speaking requires Pareto optimality. Since the first fundamental welfare theorem[22] states that any perfectly (i.e., in absence of market failures) competitive market equilibrium is Pareto efficient, competitive financial markets would be, generally speaking, allocatively efficient. Second, markets are operationally efficient —a.k.a. internally efficient markets— when participants can execute transactions and receive services at a price that reflect the actual costs required to provide them, such that no excessive frictional costs reduce the risk-return profile of transactions. That requires transaction costs to be determined competitively (Blake, 2000).

Allocative and operational efficiencies refer to the market microstructure. Since competitive markets are a sufficient condition to satisfy both allocative and operational efficiencies, the debate about whether markets are efficient has eventually become a debate about informational efficiency. Indeed, when the financial literature speaks of market efficiency it is generally talking about informational efficiency alone. Nonetheless, we must be aware that once we depart from neoclassical equilibrium, a market may be informationally efficient yet allocatively inefficient (Bouchaud et al., 2008).

A classic definition of an informationally efficient market is the one where the information set is identical to all investors, in a way security prices fully reflect all available information and they instantaneously and fully adjust to every new piece of information (Blake, 2000). This statement is known as the **Efficient Market Hypothesis (EMH)**. The original definition was set by Eugene Fama, who defines efficient markets as those where prices fully reflect available information (Fama, 1970) or,

---

[21] Perfect competition requires a decentralized market with no barriers to entry or exit, where participants have no market power to set prices, and where they have equal access to the production technology (Novshek and Sonnenschein, 1987). The absence of frictions requires, among others, no taxes, no transaction costs, no operative limits and no externalities.

[22] The first fundamental welfare theorem states that under certain (ideal) conditions, the competitive economy is always Pareto efficient, in the sense that no one can be made better off without making someone else worse off (Stiglitz, 1991). A market result that is below the best possible result is a market failure (Lipsey, 1989). It may occur because of public goods, imperfect knowledge, differentiated goods, concentrated market power or externalities.

alternatively, those where there are large numbers of rational, profit-maximizers actively competing, each of them trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. These markets lead to a situation where security prices today reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future (Fama, 1965a).

An alternative interpretation of market efficiency is summarized by Jensen (1978) and Granger (1992). For Jensen (1978), the EMH is in essence an extension of the zero profit competitive equilibrium condition from the certainty world of classical price theory to the dynamic behavior of prices in speculative markets under conditions of uncertainty. This way, a market is said to be efficient with respect to an information set Ω_t simply if it is impossible to make economic profits by trading on the basis of information set Ω_t. Likewise, Granger (1992) considers that mere forecastability is not enough: for a market not being efficient, traders should be able to obtain economic profits in the sense of risk-adjusted returns net of all costs. Richard Roll puts it shorter: what the EMH asserts is that *there is no free lunch*, particularly in financial markets.[23] Efficiency would be satisfied as long as none trading techniques are more profitable than a buy-and-hold strategy.

However, the original and alternative definitions of market efficiency are not equivalent. Statman (1999) highlights the difference: the term market efficiency has two meanings: one is that investors cannot systematically beat the market, the other is that security prices are rational, meaning they reflect only fundamental or utilitarian characteristics —such as risk— but not psychological or value-expressive —such as sentiment. This is a classic critique that may be traced back to Shiller (1984): unpredictability does not imply prices are rational. We leave further insight on this critique to Section 2.3.

Whatever definition of informational efficiency we use, there is a point in common: prices always adjust, fully and instantaneously, to new information available. An efficient market is not an unerring mechanism to prophesy future: it is an unbiased predictor of an asset's intrinsic value *given information available*. Markets will be efficient if their pricing mechanism provides agents with prices that fully reflect all information available and adjust immediately to any new data being published. Investors *rationally* analyze information and estimate a subjective expected security price. In an uncertain world, the intrinsic value —defined as the present value of all the asset's expected cash flows in the future— can never be determined exactly, so it would be different to each investor, even if they all have the same information available. But in an efficient market, competition among agents will make multiple expectations of the asset's value wander randomly about its intrinsic value (Fama, 1965a). Otherwise, if discrepancies between price and intrinsic value are systematic, not random, rational agents (known as arbitrageurs) will exploit those differences —thus obtaining a riskless profit— to make them disappear.

[23] Richard Roll's foreword to Lo (1997).

Hence, Fama (1970) asserts efficiency would hold as long as there is a sufficient number of rational investors that have access to available information and exploit those price discrepancies.

Following this, the rationalists have classically interpreted the two definitions of EMH —unbiased estimator and price unpredictability— as equivalent. The seminal papers of this interpretation are Samuelson (1965) and Fama (1965a). Samuelson proves that properly anticipated prices fluctuate randomly. Put it simple, in an informationally efficient market, prices reflect all that is predictable; hence price changes must reflect only new, unpredictable information. Fama (1965a) states that if prices instantaneously and fully reflect all relevant information, security prices will wander randomly about its intrinsic value —hence prices will be good estimators of fundamental values. If not, the difference between actual price and the security's true value will be small enough such that, given transaction costs, that difference cannot be exploited profitably.

Consequently, an efficient market is considered to be a *fair game* where all investors, using the information available to make their expectations about future prices, have the same possibility to win or lose. In a fair game there is no systematic difference between the actual return on the game and the expected return before the game is played.[24] Mathematically

$$r_{i,t+1} = E\left(r_{i,t+1}|\Omega_t\right) + \varepsilon_{i,t+1}\,, \tag{2.1}$$

where $r_{i,t+1}$ is the actual return on security *i* in period *t+1*, $E(r_{i,t+1} \mid \Omega_t)$ is the expected return on security *i* in period *t+1*, conditional on the set of information available in period *t*, Ω_t, and $\varepsilon_{i,t+1}$ is the prediction error on security *i* in period *t+1*. One consequence is that, if EMH holds, markets will be in a *continuous stochastic equilibrium*: return on securities will change randomly to new information available, since new information comes in a random fashion. Market efficiency would imply the randomness of security price series, and that is the reason why, since Bachelier (1900), efficiency has been classically modeled to test the hypothesis that prices follow a random walk or other types of random series.

To sum up, the Efficient Market Model (EMM) asserts that asset prices are determined by investors' expectations on future cash flows (coupons, dividends) discounted to present, with expectations conditioned on information available, $E(\cdot|\Omega_t)$.[25] Hence, (informational) efficiency essentially depends on three critical features: **expectations**, **information** and the **discount factor**. These are the concepts we need to interpret to understand market efficiency. We analyze them next.

2.2.2. Expectations

Keynes (1936) pioneered to point out the importance of expectations, contributing at least in two ways. First, in analyzing their effects on interest rates and unemployment, he differentiated short-term and

---

[24] Alternatively, a fair game is one in which the value of a play is zero (von Neumann and Morgernstern, 1944).

[25] Alternatively, in Shiller (2003)'s words, the EMM asserts that *"the price of a share equals the mathematical expectation, conditional on all information available at the time, of the present value of actual subsequent dividends accruing to that share"* (p. 85) while the EMH posits that price equals the optimal forecast of that present value of future dividends.

long-term expectations to suggest their effects might persist over time. Second, Keynes suggested that economic instability may be a consequence of psychological characteristics of people: the *animal spirits* would dominate human decision-making, and so most of our activities would depend on spontaneous optimism rather than on a mathematical expectation. This relationship between psychology and economics would be assumed decades later by the behavioral economics.

Nonetheless, it was Grunberg and Modigliani (1954) who first noticed that expectations of future events play an essential role in economics they do not play in physical sciences. Thus, our understanding of economic events is bounded by our limitations to explain the role expectations play in decision-making. In particular, they investigate whether social sciences would be limited to predict both publicly and correctly —since, in reacting to a *public prediction*, individuals might influence the course of events and thereby falsify the prediction.[26]

Early models assumed agents make systematic biases. These include, among others, the Cobweb theorem,[27] the adaptive expectations (Cagan, 1956), and the extrapolative expectations (Duesenberry, 1958). When analyzing the monetary dynamics of hyperinflation, Cagan suggested agents use past prediction errors to reassess their expectations about the future value of the variable. Duesenberry, instead, suggested the persistence of business cycles would be a consequence of agents extrapolating their expectations, in the sense that they believe past price increases would continue in the future. Extrapolative and adaptive expectations were criticized for assuming agents only use past performance to predict future performance and for assuming agents do not learn from their mistakes. Rational expectations (Muth, 1961) would succeed to overcome these objections.

Rational expectations

The rational expectations hypothesis is generally regarded as the best model to analyze dynamic economic processes. Under this setup, alternative hypotheses suggesting that systematic biases may appear are interpreted as anomalies. An antecedent is the analysis by von Neumann and Morgenstern (1944) of economic decisions in the context of a theory of games. They interpreted rational behavior as the players' optimal strategies given the alternatives and possible outcomes of a pre-specified game. The game solution requires that each participant accounts for every possible conduct of other participants,

---

[26] Grunberg and Modigliani conclude that a correct public prediction is conceptually possible: if the agents' reaction to public prediction alters the course of events, the reaction can conceptually be known in advance and taken into account.

[27] The Cobweb theorem was originally proposed simultaneously by Schultz (1930), Tinbergen (1930) and Ricci (1930), and enhanced by Lundberg (1937), Ezekiel (1938), Samuelson (1948) and Schneider (1948). Here we follow Akerman (1957)'s interpretation: take an agricultural market under conditions of pure competition and in an original state of equilibrium at a given price, where once plans are made farmers require at least one whole period to change production levels. Here, if some sort of disturbance occurs (e.g., unusual weather causing exceptionally small crops) it would give rise to a discrepancy between actual demand and supply, such that a higher price is set. The Cobweb theorem assumes a situation where a permanent enlargement of a crop will, for different reasons, cause some additional cost. Such cost will be undertaken only if the higher price is expected to be of a permanent nature, but farmers will convince themselves that the new price will remain high only after several years. The rise in prices in period 1 will, therefore, cause an increase in supply in period 2 considerably lower than the one that would clear the market. Prices and production levels would gradually adjust during a series of periods until a new equilibrium is reached, graphically forming a kind of spider net or 'cobweb'.

as well as the influence of chance events. Muth (1961) formalized this rational behavior into a model: the rational expectations hypothesis. Since expectations would be informed predictions of future events, they should be essentially the same as the predictions of the relevant economic theory. In particular, the rational expectations hypothesis asserts three things. First, information is scarce, so the economy does not waste it. Second, the way expectations are formed depends on the structure of the relevant economic theory. Third, a public prediction in the sense of Grunberg and Modigliani will have no substantial effect on the operation of the economic system —e.g., on how prices are formed in financial markets— unless it is based on insider information.

A key assumption behind the rational expectations hypothesis is the *Harsanyi doctrine* (Harsanyi, 1967). In their theory of games, von Neumann and Morgenstern categorized games of complete and incomplete information, as well as games of perfect and imperfect information,[28] but assumed complete information without any further discussion. The theory of games with incomplete information made little progress since then, until Harsanyi (1967). Harsanyi highlights that games with incomplete information *"appear to give rise to an infinite regress in reciprocal expectations"*: sellers of an asset should have expectations on buyers' expectations, but buyers also have expectations on other potential buyers, so sellers should have an expectation on buyers' expectations on potential investors… and so on. These sequential–expectations models for games with incomplete information are known as *Keynesian beauty contests*, after Keynes (1936).[29]

Harsanyi proposes a solution, known as the *Harsanyi transformation*: for any given I-game G (an incomplete information game, G), some C-game G* (a complete, but imperfect, information game) can be constructed that is equivalent to G. This is done by introducing Nature as a player: we treat a player who has different payoffs under different circumstances as a player of different types, involving random events assumed to occur before players choose their strategies (i.e., *Nature moves first*). To show the C-game G* is equivalent to I-game G, Harsanyi assumes each player assigns a *subjective*[30] joint probability

[28] On one hand, for a description of a game to be complete, specifications about the state of information, payoffs and strategies available to every player at each decision point have to be set. On the other hand, games of perfect information require that any player making a move M_k has to be informed about the choices of all preliminary moves $M_1,M_2,...,M_{k-1}$ in the game. Chess is a typical representative of games with perfect information. Preliminarity is a requisite for perfect information, but anteriority does not mean preliminarity: in games of imperfect information the player who makes the move M_k is not informed about everything that happened previously. Poker is a good example of games with imperfect information. These games are strongly influenced by the players' strategies and signaling —that is, the spreading of true or false information to other players.

[29] Keynes described price fluctuations in equity markets as a consequence of investors' iterative expectations like in a beauty contest. In this type of contests, a naive strategy would be to choose the faces most beautiful to the entrant. In order to maximize the chances to win the prize, a more sophisticated strategy for a rational player would be *"anticipating what average opinion expects the average opinion to be"* about beauty, based on some inference from his knowledge of public perception.

[30] If probabilities are assumed to be *objective*, like in the Von Neumann–Morgenstern theory, we are assuming randomness and probabilities do "exist" in Nature. This objectivist position was set by Laplace (1774), the *relative frequentist* view by Mises (1928) and Reichenbach (1949a,b) —related to Bernoulli's (1713) law of large numbers— and the *propensity* view by Peirce (1910) and Popper (1959). Many statisticians and philosophers objected to this view, arguing that probabilities are an epistemological and not an ontological issue: they are a measure of the lack of knowledge about the conditions which might affect a so-called random event, and thus merely represent our beliefs about it. Ramsey (1926) asserted that probability is related to the knowledge possessed by a particular individual alone. Probability would be, this way, *subjective*. The difficulty was to derive mathematical expressions for probabilities from personal beliefs, but Ramsey suggested a way to do it. De Finetti

distribution to the variables they ignore, and shows we can find a natural analogue of the I-game G, a C-game G* with the same payoff functions and the same strategy spaces where the information or attribute vector of each participant are reinterpreted as random vectors (chance moves) with an *objective* joint probability distribution. Hence, both games will be Bayes–equivalent, a postulate known as the Harsanyi Doctrine:[31] *"every player will use his* ***subjective*** *probabilities exactly in the same way as he would use known* ***objective*** *probabilities numerically equal to the former"* (p. 174). The postulate implies that if all agents have the same knowledge, then they ought to have the same subjective probability assignments. This assertion is nowhere implied in the Ramsey-de-Finetti subjective probability theory, but it lies in the background of the rational expectations hypothesis.

Several authors argued against Harsanyi doctrine. Morris (1995) criticize the use of the common prior assumption and the unwillingness of economists to use truly subjective probabilities the same way we accept the idea of a personal utility function. Biais and Bossaerts (1998) assert that the Harsanyi transformation holds not because of the common prior assumption, but only if agents use the same rule to form their expectations. However, a strength of the model is that rationality is an assumption that can be modified (Muth, 1961). Systematic biases, poor memory, incomplete or incorrect information, etc. may be examined under the assumption that agents *generally* behave rationally. Hence, the rational expectations hypothesis has been widely accepted in the context of market efficiency and beyond: the debate on money neutrality (Lucas, 1972), the effectiveness of alternative monetary policies (Sargent and Wallace, 1975; Barro, 1976), real business cycle models (Lucas, 1975; Kydland and Prescott, 1982), etc. Nonetheless, some of its limitations have been outlined. Some critiques come from the behavioral literature, hence will be reviewed in Chapter 3. Others are reviewed in the remainder of this section.

Critiques to rational expectations

A classic in the literature is the concept of bounded rationality (Simon 1955, 1959). Simon criticizes the assumption of rationality because it leads to theories unable to explain the observed phenomena. He suggests instead people should be viewed as *boundedly rational*, where utility maximization is replaced by satisficing: information is vast but we have limited information–processing abilities, hence we construct simplified models of the world to make decisions. Following this, Haltiwanger and Waldman (1985) provide a model where agents are heterogeneous in terms of information processing abilities.

Together with bounded rationality and information processing limits, the rational expectations hypothesis has been criticized for two other reasons: the effects of incomplete, imperfect or costly information on one hand, and the possibility of speculation on financial markets on the other. In regards

(1931, 1937) suggested a similar derivation. The Ramsey-de Finetti approach says that subjective probabilities can be inferred from observation of people's actions, a *revealed belief* akin to the revealed preference approach in consumer theory. The Ramsey-de Finetti was developed into a full theory by Savage (1954)'s *Foundations of Statistics*.

[31] The Harsanyi doctrine is also known as the 'common prior' assumption, because the lottery played by Nature occurs prior to any other move in the game.

to the former, information is rarely costless, measured either in terms of money, time or effort. This may make different market participants have access to different information sets (see subsection 2.2.3), but also affect how expectations are formed. Feige and Pearce (1976) observe agents base their expectations about inflation only on a subset of data readily available, due to the cost-benefit trade-off of searching for additional information. They call these expectations *economically rational*. Copeland (1989) suggests a similar idea for currency markets and names them *weakly rational expectations*: a variable's expected value, conditional on an information set that contains only the past history of the variable.

Speculation, defined as investors buying a stock now in order to sell it later for more than what they think it is actually worth (Harrison and Kreps, 1978), goes against the rational prices interpretation of EMH: if investors have rational expectations, why would they speculate? Harrison and Kreps (1978) set one of the first and most relevant papers in behavioral finance with a model of speculation based on overconfidence and heterogeneous beliefs. According to it, if investors may form different opinions even when they have the same information, there can be no objective intrinsic value for the stock. Instead, intrinsic values would be obtained through market aggregation of the diverse investor assessments. The main result is that different levels of optimism across investors make financial assets carry a speculative premium: holding a stock gives the owner the option to resell it to someone more optimistic. Speculators would then base their expectations on interactions among agents rather than on relevant information about the true value of a security (Peters, 1991). This would make speculative markets inefficient in the sense they are not unbiased predictors of an asset's true value. Furthermore, random time series would not necessarily imply efficiency (Black, 1986): noise causes markets to be inefficient, but often prevents us from taking advantage of inefficiencies, and makes it difficult as well to test the theories about the way financial markets work. *"We are forced to act largely in the dark"* (p. 529).

In the end, the debate on expectations and speculation leads to the Harsanyi doctrine of a common prior. Aumann (1976) shows people with the same priors and common knowledge about a future event cannot agree to disagree about such event, excluding the possibility of a purely speculative trade among them (Bossaerts, 1995). Shiller (1995) analyzes some opinion polls of investors about their expected prices in equity markets, and concludes that a mutually recognized disagreement among them is clear. Now, if we deviate away from the common prior assumption and admit agents may agree to disagree, the distribution of beliefs in the economy is not common knowledge, agents update higher-order beliefs like in the Keynesian beauty contest, and the computation of equilibria becomes intractable.[32]

[32] Early efforts to solve this problem include Böge and Eisele (1979) and Mertens and Zamir (1985), who prove an equilibrium exists in static games with infinite beliefs hierarchies, and El-Gamal (1992), who does the same for dynamic models without strategic interactions, assuming agents agree from a certain order on. Biais and Bossaerts (1998) analyze instead an *average opinion rule* they claim to be consistent with Muth's original description of rational expectations: prior to the game, agents consider their own private valuations to be average, and to do so, they first analyze what they think other investors' private valuations are on average. When agents disagree on the speculative value of an asset, some trading patterns (known as *controversial trades*) may arise. The impact of such controversial trades on trading volume and return volatility would not be significantly different compared to those under the common prior assumption.

Despite these criticisms, rational expectations have also succeeded to explain speculation and market efficiency. Kodres and Pritsker (2002) develop a multiple asset rational expectations model of asset prices that explains financial market contagion. Condie and Ganguli (2011) prove the existence of fully-revealing rational expectations equilibria for almost all sets of beliefs when investors are ambiguity averse and have preferences that are characterized by Choquet expected utility. The paper extends the works of Radner (1979) and Allen (1981, 1982), who show that smooth preferences imply generic full revelation and provide conditions for informational efficiency under ambiguity.[33]

2.2.3. Information

Information is the key concept in the formulation of the EMH, as it refers to whether prices fully reflect available information. Two topics are essential: first, to know which are the relevant contents of the information set for market efficiency; second, to analyze which market participants have access to that set and to which extent. The interpretation of these two topics would lead Fama (1970) to propose three different degrees of efficiency. Consequently, in what follows we describe the information set, market participants' access to information, and the three degrees of efficiency in the EMH.

Information set

The relevant information set for market efficiency, denoted Ω_t in Eq. (2.1), is the one that conditions agents' expectations on asset prices. Fama (1965b) theorized it should include two subsets: events that have already occurred and events which, as of now, the market expects to take place in the future. Considering the information in these two subsets, market participants make their bets on the intrinsic value of securities. In addition, intrinsic values change over time because the information set includes market expectations on future events and, by definition, what markets expect changes if new relevant information is available. Competition in an efficient market will, *on average*, make changes in the intrinsic value due to new information to be reflected *fully* and *instantaneously* in prices (Fama, 1965b). We emphasize three words —on average, fully and instantaneously— because under uncertainty we should not expect market prices to adjust immediately and exactly at the proper size. Prices may over and underreact, and their changes may also precede or lag the occurrence of the event that made intrinsic values change. Nonetheless, for market efficiency to hold, overreaction will happen as often as underreaction, while the lag period for prices to adjust to new intrinsic values will be itself an independent random variable.

---

[33] Further research on rational expectations may be found, among others, in the works of Givoly (1985), who finds evidence that financial analysts' earnings forecasts are rational in the sense they use available information, but adaptive in the way they form those forecasts; Bray and Savin (1986), who investigate whether agents can learn how to form rational expectations using standard econometric techniques; Hamilton (1988), who performs a rational expectations econometric analysis of the term structure of interest rates; Veronesi (1999), who provides an asset pricing model where investors' willingness to hedge against uncertainty explains overreaction to bad news in good times and underreaction to good news in bad times; Beeby, Hall and Henry (2001) who analyze whether the specification of the learning rule in macroeconomic models is arbitrary; and Pearlman and Sargent (2005), Allen, Morris and Shin (2006) and Bacchetta and van Wincoop (2008), who analyze iterative expectations.

The consequence of this adjustment property of efficient markets is that successive price changes of a given security will be independent and identically distributed. Thus, the best estimation of the return on a security tomorrow is the return on the security today. Mathematically,

$$E\left(r_{i,t+1} | \Omega_t\right) = r_{i,t} \, . \tag{2.2}$$

Substituting (2.2) in (2.1) we have market returns in efficient markets must follow a random walk (i.e., a *martingale*),[34]

$$r_{i,t+1} = r_{i,t} + \varepsilon_{i,t+1} \, . \tag{2.3}$$

Security prices, instead, are expected to drift upwards —since no one would invest in risky securities unless they offered a positive expected return. Consequently, prices would follow a *submartingale* (a random walk with a positive drift).[35] Mathematically,

$$P_{i,t+1} = P_{i,t} + g_{i,t+1} + \varepsilon^*_{i,t+1} \, , \tag{2.4}$$

where the positive drift, g, would be a random variable as well, such that $g_{i,t+1} = r_{i,t+1} \cdot P_{i,t}$.

In well-functioning markets, market forces would make the positive drift equal to the required return for securities of the same level of risk. Therefore, we interpret (2.4) as the security price series adjusted for required returns (Jensen, 1978). Indeed, Fama (1970) claims that the random walk model is a more detailed extension of the fair game efficient markets model. The latter only says that the conditions of a market equilibrium can be stated in terms just of expected returns, thus it says little about the stochastic process that generates these returns. The random walk model, instead, requires that the conditional and marginal probability distributions of an independent random variable are identical. In consequence, empirical tests of the random walk model would be more strongly in support of the EMH than tests of the fair game properties. A consequence of the random walk property is that price series should have *no memory*, meaning historic prices cannot be used to predict future price movements or, at least, they cannot increase the expected gains above those expected for a naive buy-and-hold strategy.

Market participants' access to information

The second crucial topic to define the role of information in the EMH is to analyze which market participants have access to it and to which extent. In particular, we will focus on two aspects that are relevant to determine the different degrees of market efficiency: whether some agents might profit from private inside information, and whether markets might not adjust instantaneously to new information when it is costly. The EMH assumes information is costless and identical to all investors. However, what

[34] Security returns follow a martingale *"when the expected rate of return on stock conditional on past realized rates of return is always equal to its unconditional expectation"* (LeRoy, 1973, p. 436).

[35] Security prices follow a submartingale whenever $E\left(P_{i,t+1} | \Omega_t\right) \geq P_{i,t}$ holds.

happens if it does not? Fama (1970) admits that *"a frictionless market in which all information is freely available and investors agree on its implications is not descriptive of markets in practice"* (p. 387). Nonetheless, having costless information available to all market participants is only a sufficient, not necessary, condition for market efficiency.[36] Therefore, markets where information is not costless and not identical to all investors can still be efficient if there is a *sufficient number* of rational investors having ready access to available information so they can profit from discrepancies between prices and intrinsic values. A question remains open about how many investors are sufficient enough.

Accepting information may be costly leads to several arguments against EMH. Here we consider five: the possibility for insider traders (i.e., investors having access to private information) to make excess profits, whether competitive markets may reach an equilibrium, whether financial analysis may be profitable or not and the impossibility of informationally efficient markets, the extent to which prices are informative, and the extent to which they adjust instantaneously or not to new information revealed. They are reviewed in what follows.

If information is costly and, consequently, not all investors have the same information available, asymmetric information problems may appear. Two consequences follow. First, there is a possibility for *insider trading* to be profitable. Second, the assertion that competitive markets reach an equilibrium is now disputed. Grossman and Stiglitz (1980) highlight that, if prices in equilibrium eliminate potential arbitrage profits, then no competitive markets would be in equilibrium at any time when arbitrage is costly. The competition between informed arbitrageurs and *noise traders* would lead to an 'equilibrium degree of disequilibrium': prices would reflect the information of arbitrageurs but only partially.

Jensen (1978) then modifies the strict interpretation of costless information. Markets are efficient if it is impossible to make economic profits trading on the information set available, where economic profits mean 'risk-adjusted returns net of all costs'. However, if the benefits of fundamental analysis are lower than its costs, why would financial analysts be willing to spend time and money on it? Moreover, the incontestable evidence that financial analysts do exist may be argued against Jensen's interpretation of EMH. Market efficiency would imply prices reflect available information only to the extent that the marginal benefits of exploiting the information exceed the transaction costs incurred in doing so, but Jensen's interpretation puts a limit to that possibility.

Grossman (1976) and Grossman and Stiglitz (1976, 1980) work on that contradiction to suggest the impossibility of informationally efficient markets: *"if the market aggregated information perfectly,*

---

[36] Fama (1970) reckons three sufficient conditions for capital market efficiency, the other two being the absence of transaction costs in trading and that all market participants agree on the implications of information on future prices. Again, these are neither necessary conditions: large transaction costs do not imply that, when trades take place, prices will not fully reflect available information; disagreement among investors about the implication of information on intrinsic values does not itself imply market inefficiency unless there are investors who can consistently make better evaluations of available information than what is implicit in market prices.

individuals' demands would not be based on their own information, but then, how would it be possible for markets to aggregate information perfectly?" (Grossman and Stiglitz, 1976, p. 250). Grossman and Stiglitz (1980) show that, in markets with both informed investors and noise traders, the number of individuals who choose to be informed becomes an endogenous variable of the model. When informed investors pay for research, the price mechanism conveys information from informed to noise traders. This makes publicly available the information informed investors had paid for, but only imperfectly *"for were it to do it perfectly, an equilibrium would not exist"* (p. 393). If prices fully revealed information, nobody would pay for it; if they choose to be uninformed, markets are plenty of profit opportunities.[37] All equilibria that might exist are a sort of equilibrium degree of disequilibrium where some agents are informed, others are not, and prices imperfectly convey information.[38]

A final argument against EMH that follows if the cost of collecting and processing information is non-negligible is that, since time and money is required for analysts to process information, markets would not necessarily adjust instantaneously to new information. Instead, the adjustment would occur only after a certain period of adaptation or learning by the market.

Degrees of efficiency

We have seen that the contents of the information set include information about past events and about events the market expects to take place in the future. When new information is available, efficient markets are expected to fully and instantaneously incorporate them on prices. Besides, we discussed that if information is costly it would introduce asymmetries of information that might challenge EMH in at least two instances: the possibility for some agents to profit from private inside information, and the extent to which markets would not instantaneously adjust to new information.

One of the contributions of Fama (1970) —and previously Roberts (1967)— was to anticipate that the proper answer to the question 'are markets efficient?' might not be a binary variable "yes/no". Instead, he defined three degrees of efficiency —weak, semi-strong and strong— that take into account the topics considered above. Fama argued expectations could be conditioned on three subsets of

---

[37] The more individuals are informed, the more informative becomes the price system, but at the same time the excess return informed traders can obtain is reduced. The equilibrium number of agents who choose to be informed depends on three parameters. First, the higher the cost of information the smaller the equilibrium percentage of informed individuals. Second, the higher the quality of the informed trader's information, the more informative the price system will become. However, the equilibrium proportion of informed to uninformed individuals may increase or decrease, because even though the value of being informed increases with the quality of the information, the value of being uninformed also rises when the price system becomes more informative. Third, the greater the magnitude of noise the less informative the price system will be, so in equilibrium the greater the noise, the larger the proportion of individuals that will choose to be informed.

[38] Some authors enhanced this argumentation. Hellwig (1980) suggests prices do not depend only on the information vector but also on agents' preferences (i.e., the strength of the agent's reaction to information). Two consequences follow. First, the less risk averse an agent is, the more relatively important the information vector will be. Second, in large markets the equilibrium price will only reflect pieces of information that are common to a large number of agents. Therefore, a market will fully aggregate information only if there are many agents with many independent sources of information, so noise is filtered out and does not affect the price. However, noise is necessary for smart investors to earn profits. If information is costly, it is against noise traders —individuals who trade on what they think is information but is in fact merely noise— that smart investors earn their rents (Grossman, 1976; Black, 1986).

information. First, a *weak form* information set, which contains the historical prices of the security under consideration. Then, a *semi-strong form* information set, concerning any other information that is publicly available. Finally, a *strong form* information set, which contains both public and private inside information. The difference between the weak and the semi-strong form information sets takes into account the distinction between information about past events and events the market expects to take place in the future. The second subset, the semi-strong form, also takes into account the extent to which markets would not instantaneously adjust to new information revealed. Finally, the difference between the semi-strong and strong form subsets accounts for the possibility that some agents might profit from private insider information.

Based on these three subsets of information, Fama (1970) proposed three versions of the efficient market hypothesis to be tested. They follow in order:

- The *weak form EMH* states that security prices fully reflect all past information contained in the historical series of prices. Hence, no investors will be able to consistently outperform founding their investment decisions on the analysis of past prices and trading volumes. In a weak-form efficient market, security price series behave as a random variable, markets have no memory, and technical analysis or any other trading techniques based on the analysis of historical prices will be of no value. Tests of the weak form EMH usually involve serial correlation analysis, as we shall see in Section 2.4.
- The *semi-strong form EMH* states that prices fully reflect all publicly available information and, in consequence, they instantaneously and fully reflect any changes in such information set. When new information that affects the intrinsic value of a security becomes publicly available, competition will force the effects to be, on average, fully and instantaneously incorporated into prices. In a semi-strong form efficient market no investors will be able to systematically outperform the average market return through the analysis of publicly available information. Hence, fundamental analysis would be worthless. Tests of the semi-strong form EMH try to identify market *anomalies* where a rationale for rational behavior of market participants could not be vindicated.
- The *strong form EMH* states that prices instantaneously and fully reflect information, including not only publicly but privately available inside information too. Markets would respond so quickly to investors trying to profit out any piece of inside information they own, that they would not be able to take advantage of it. Tests are usually conducted through a performance analysis of market participants expected to have access to inside information, such as mutual fund managers or executives of companies quoting at the markets.

In Section 2.4 we will provide a summary of the different tests that are performed to account for the three levels of efficiency in financial markets, as well as a review of some relevant articles.[39]

2.2.4. Discount factor

One of the central tenets of modern financial economics is the tradeoff between risk and expected return. However, the early version of the EMM only focused on expected returns and did not account for risk in any way (Lo, 1997). As we saw, the EMM asserts that asset prices are determined by investors' expectations, conditional on all information available at the time, of the present value of the expected future cash flows. The best predictor of future return would be today's return —i.e., market returns are a martingale, see (2.3)— while security prices would follow the submartingale in (2.4): they drift upwards because no one would invest in risky securities unless they offered a positive expected return.

In his search for a plausible way to test the EMH, Fama (1970) noticed has empirical content only within the context of a more specified model of price formation and market equilibrium. Thus, he suggested to use asset valuation models like the Sharpe–Lintner CAPM to estimate the drift in (2.4) —i.e., the expected return investors require to invest in stocks. The CAPM posits that such expected return is a function of its risk. However, different theories differ primarily on how risk is defined —CAPM, for instance, uses beta to measure the risk premium one expects to be paid for. Besides, the assumption that market equilibrium can be stated in terms of expected returns, where the value of the equilibrium expected return $E(r_{t+1}|\Omega_t)$ would be determined from the particular expected return theory at hand, also introduces a joint hypothesis problem that will be later discussed (see subsection 2.3.2).

Fama and MacBeth (1973) offered the first test of the CAPM, introducing the Fama–MacBeth regressions for parameter estimation.[40] Then, Merton (1973b) extended the CAPM to an intertemporal general equilibrium model based on consumer–investor behavior where investors maximize the utility of lifetime consumption. Subsequent models showed that rational asset prices may have a forecastable element that is related to the forecastability of consumption (Lucas, 1978) and that a stock's risk premium (beta) would also depend on per capita consumption (Breeden, 1979). At that point, the discount factor efficient markets would use to compute the present values of future cash flows was interpreted to be equal to the intertemporal marginal rate of substitution for consumption that Merton,

---

[39] Further references on information and market efficiency may be found. Classic works include Granger and Morgenstern (1970) on predictability of stock prices, Rothschild and Stiglitz (1976) on market equilibrium under imperfect information, Stiglitz (1982) on the inefficiency of incomplete markets, He and Wang (1995) and Kandel and Pearson (1995) on trading volume and information flow in markets with informational asymmetries among investors. Among recent literature, some relevant articles are in order. Marín and Rahi (2000) develop a theory of endogenous market incompleteness. Amato and Shin (2003) analyze how central bankers disclosures on monetary policy shape agents' expectations when agents have diverse private information. Kasa, Walker and Whiteman (2006) develop a dynamic asset pricing model with persistent heterogeneous beliefs, and characterize the resulting high-order belief dynamics. Cespa and Vives (2009) investigate the dynamics of prices, information and expectations in a competitive, noisy, dynamic asset pricing model, and find two possible outcomes, Keynesian —with prices far away from fundamentals— and Hayekian. Biais, Bossaerts and Spatt (2010) develop a theory of capital markets and portfolio choice under asymmetric information.

[40] These regressions are a particular case of the Generalized Method of Moments, GMM, by Hansen (1982) that we will later describe.

Lucas and Breeden were using to derive stock returns in their models. Besides, the relevant risk factor that would explain the expected return of a stock was the sensitivity to the market according to the updated CAPM versions.

However, Fama would later endorse two additional risk factors. The empirical literature had identified two categories of stocks that seemed to outperform the market. The first category was small-cap stocks (Banz, 1981). Banz conjectured that the availability of corporate information is related with the firm's size and so investors would require additional returns to invest in small-cap firms to compensate for that risk. He then found empirical evidence that small caps beat the market over long horizons. The second evidence was that value stocks —stocks with low ratios of price to a fundamental like book value (P/B), cash flow (P/CF) or earnings (P/E)— have higher average returns than growth stocks, which have higher ratios of price to fundamentals (DeBondt and Thaler, 1985; Fama and French, 1992). In particular, Fama and French (1992) confirmed the empirical contradictions of the CAPM: variables that have no special standing in asset-pricing theory —namely, size, leverage, book-to-market-equity and earnings-to-price ratios— show reliable power to explain the cross-section of average returns. When β is unrelated to size, they find no relation between β and average return, contrary to CAPM. Instead, they find clear evidence on the robustness of the size effect and an even more powerful book-to-market effect. Furthermore, leverage ratios are captured by the book-to-market ratio, whereas the combination of size and book-to-market absorbs the apparent role of E/P in average stock returns.

As a result of these two findings, the size effect and the book-to-market effect, Fama and French (1993) propose a three-factor model for stock returns: the expected returns would respond to three risk factors, associated with size, value versus growth (book-to-market ratios) and sensitivity to the market.[41] In addition, Fama and French (1993) identify two factors for bonds, related to maturity and default risks.[42] More specifically, the expected excess return on portfolio *i* under the three-factor model would be explained by the sensitivity to three factors,

$$E(R_i) - r_f = b_i \cdot \left\lfloor E(R_M) - r_f \right\rfloor + s_i \cdot E(SMB) + h_i \cdot E(HML) \ , \tag{2.5}$$

namely, the excess return of the market portfolio (R_M - r_f), the difference in return between a portfolio of small stocks and a portfolio of large stocks (SMB, small minus big), and the difference in return between a portfolio of high-book-to-market stocks and a portfolio of low-book-to-market stocks (HML, high minus low). Fama and French (1996) obtain some results, consistent with the intertemporal CAPM (Merton, 1973b) and APT asset pricing (Ross, 1976), that would explain the most significant anomalies

[41] Recently Fama and French (2012) seem to have subscribed as well to a classic in the behavioral literature, the evidence that stocks may exhibit momentum: stocks that have done well over the past year tend to continue to do well (Jegadeesh and Titman, 1993; Griffin, Ji and Martin, 2003). Nonetheless, rationalists interpret this would be explained by risk factors that affect firm investment life cycles (see *momentum* strategies in Chapter 4).

[42] In this paper, Fama and French use a time series regression approach instead of the cross-section regressions used in Fama and French (1992). The reason is that it would be difficult to add bonds to the cross-section regressions since size and book-to-market equity would have no obvious meaning as explanatory variables for returns on government or corporate bonds.

identified in the academic literature except momentum. Further research would support their results: for instance, Kothari and Shanken (1997) find evidence that book-to-market and dividend yield track time-series variation in expected real stock returns, whereas Pontiff and Schall (1998) find the book-to-market ratio of the DJIA index predicts both broad market returns and small firm excess returns.

Excess volatility

In early 80s, the literature on excess volatility came to contradict the tenets of the EMM in regards to risk in financial markets. The articles by Shiller (1979, 1981) represent a groundbreaking research in behavioral finance: they impose a theoretical limit on bond and stock market volatility that were largely violated according to empirical data observed. Shiller (1981), in particular, shows stock prices are too volatile to be justified by new information about future real dividends. This finding would put into question the basics of the entire efficient markets theory (Shiller, 2003), as it implies that changes in prices occur for no fundamental reason, just animal spirits of mass psychology.

The research on excess volatility on stock markets interprets the EMM applying a dividend discount model (DDM) to estimate the present value P_t^* of future dividends accruing to a share. Different forms of the EMM differ in the choice of the discount rate to compute the present value, but the general EMM can be written just as

$$P_t = E_t P_t^* \; , \tag{2.6}$$

where E_t refers to the mathematical expectation conditional on public information available at time t. Then, it follows from the EMM that

$$P_t^* = P_t + \varepsilon_t \; , \tag{2.7}$$

where ε_t, the forecast error, must be uncorrelated with any information available at time t and, consequently, also with P_t. Since the variance of two uncorrelated variables is the sum of their variances, and the variance of ε_t cannot be negative, it follows

$$\sigma(p) \leq \sigma(p^*). \tag{2.8}$$

That is, the fundamental principle of optimal forecasting is that the forecast must be less variable than the variable forecasted (Shiller, 2003).[43] Empirical evidence showed on the contrary that the volatility of the DJIA and S&P500 price series was between five times and thirteen times greater than the highest possible volatility it should be expected when discounting dividends.

Two critiques of Shiller's 1981 paper were in terms of the stationarity of prices[44] and the use of the discount rate. In order to model the EMH, Shiller assumed the real expected rate of return on the

[43] In Chapter 4 we provide further insight on the mathematical derivation of the variance inequalities in Shiller (1979, 1981).
[44] We focus on the discount factor critique as it deals with the topic explored here. The critique on the stationarity of prices is explored in Chapter 4. For now, only mention that Marsh and Merton (1986) noticed that *"dividend smoothing could make stock prices non stationary in such a way finite sample prices appear more volatile than the present values"* (Shiller 2003, p. 87).

stock market is constant over time (Merton, 1987a). However, the discount rate in the EMM can take different forms. A first alternative is to set it equal to the interest rate. However, if we introduce time-varying interest rates in the present value formula of the EMM we find the actual price is still more volatile than the present value of future dividends, particularly during the last half century (Shiller, 2003). A more refined alternative makes the discount factor equal to the intertemporal marginal rate of substitution for consumption Merton (1973b), Lucas (1978) and Breeden (1979) used to derive stock returns in their models above mentioned. Nonetheless, Grossman and Shiller (1981) provide a plot for that present value since 1881 to find it was only loosely related to actual stock prices, and was not volatile enough to justify the prices observed unless the coefficient of relative risk aversion used in the estimations —they use a value of three— is pushed to *ridiculously high levels* (Shiller, 2003).[45]

The idea that dramatic shifts in investors' risk aversion are needed to justify seemingly erratic price performances was later adopted by Fama and French (1988a,b, 1989). Price volatility would be a consequence of changes in the equity risk premium, rather than fundamentals. However, these changes would be rational: risks in the economy can go up and investors' willingness to bear risks can go down. We provide further insight on this interpretation in what follows.

The rationalist interpretation of changes in the discount factor (risk premium)

The early formulation of the EMH by Fama assumed investors expected the same returns in all periods. Differences in price-to-fundamental ratios across firms would explain expected changes in future firms' earnings: when dividend yields —i.e., the dividend to price ratio, d/P— are high investors perceive firms will not be able to pay high dividends much longer, while low yields imply investors believe dividends will eventually rise. Anticipated changes in fundamentals would explain why ratios are high or low. This way, the dividend yields of a stock would serve to forecasts long-term future changes in the company's future dividends.

However, in the late 80s there was extensive evidence that stock returns are predictable, though the predictable component of returns was only less than 5% of return variances. Then, Fama and French (1988b) show that this ability of dividend yields to forecast stock returns is much higher —more than 25% of variance— for longer return horizons. Behaviorists argue this predictability implies market inefficiency; rationalists, however, defend it is a result of rational variation in expected returns. Fama and French (1988b, 1989), in particular, defend that long- and short-term economic conditions produce a rich mix of variation in expected asset returns.

Campbell and Shiller (1987) then provided a test for expected volatility that modeled dividends and stock prices in a more general way. Other relevant works in line with Shiller's findings are West (1988a) and Campbell (1991), while Barsky and DeLong (1993) show on the contrary that if dividend growth rates are unstationary, EMM looks closer to the data.

[45] Hansen and Jagannathan (1991) generalized a lower bound on the volatility of the marginal rate of substitution. The violation of this 'Hansen–Jagannathan bound' is regarded today as an important anomaly in finance (Shiller, 2003).

First, Fama and French (1988b) interpret that time-varying expected returns generate mean-reverting components of prices.[46] They leave the question open to whether the predictability of returns implied is driven by rationality (e.g., *"the investment opportunities of firms and the tastes of investors for current versus risky future consumption"*, p. 5) or by animal spirits. Then, Fama and French (1989) show that expected returns on stocks and bonds contain both a risk premium that is related to the business cycle. Dividend yields and default spreads forecast expected returns that are lower (higher) for stronger (weaker) economic conditions. This return predictability would have two alternative, complementary interpretations. On one hand, it may be that the variation in expected returns with business conditions is due simply to variation in the risks of bonds and stocks. On the other hand, return predictability might be a consequence of changes in discount factors due to anticipated changes in economic conditions.[47]

Since then, rationalists accept that changes in fundamentals or interest rates are often not enough to explain the volatility of markets. Instead, price movements in the short term would be a consequence of changes in the risk premium. Ever since, the discount factor condenses two elements: the investors' intertemporal marginal rate of substitution for consumption and, now also, their appetite for risk. Today, explaining why the risk premium for stocks varies is the main source of disagreement between rationalists and behaviorists: both agree P/E and d/P are good forecasters of future returns; both agree risk premium changes mostly in periods of economic stress; however, they diverge in the interpretation of whether changes in prices are rational or not.[48] Thus, under a rationalist interpretation, return predictability would be a result of variations in the discount factor: in some market circumstances the marginal investor (rationally) requires a higher risk premium to compensate for risk than in others.

Testing the volatility of the discount factor

The Nobel Prize in Economic Sciences 2013 recognizes that Fama and Shiller (and Hansen) *"laid the foundation for the current understanding of asset prices. It relies in part on fluctuations in risk and risk attitudes, and in part on behavioral biases and market frictions"*.[49] Thus, whether bubbles are rational or not is, eventually, a debate on asset-pricing models and attitudes toward risk: the EMH claims security prices are rational; behavioral finance claims instead that, beyond attitudes toward risk, risk premia

[46] This happens because, on one hand, autocorrelation of expected returns makes its variance to grow faster with the return horizon but, on the other, this growth in variance is attenuated by a discount rate effect: shocks to expected returns are associated with opposite shocks to current prices. On average, the expected future price increases implied by higher expected returns are offset by the immediate decline in the current price. Thus, the time variation of expected returns gives rise to mean reversion of prices.

[47] The latter interpretation implies that when business conditions are poor, income is low and expected returns on bonds and stocks must be high to induce substitution from consumption to investment. Vice versa, when times are good and income is high markets clear at lower levels of expected returns (Fama and French, 1989).

[48] As we have seen, informational efficiency depends on three critical features: expectations, information and the discount factor. Shiller's contribution on excess volatility was to show that the volatility of prices cannot be explained only on fundamentals (information). Consequently, it must be either the expectations or the discount factor. Behaviorists and rationalists diverge in their interpretation of whether changes in prices are due to rational expectations and rational changes in the discount factor, or not.

[49] The Prize in Economic Sciences 2013, available from http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2013/press.pdf

may be affected by psychological issues. Here, the work of the other Nobel laureate in 2013, Lars Peter Hansen, would come to shed some light on the issue. In particular, he developed the Generalized Method of Moments (GMM) that is well suited to test rational theories of asset pricing. We provide a brief explanation in what follows.

The findings of excess volatility and return predictability called for a better understanding of what drives expected returns. The line initiated by Merton (1973b) to construct dynamic asset-pricing models introduces the possibility that investors' preferences may vary over time as a result of consumption or wealth shocks, thus generating fluctuations in risk premia and return predictability (Nobel Prize, 2013). These models are known as the consumption capital asset pricing models (CCAPM). Grossman and Shiller (1981) were the first to evaluate them quantitatively, showing that the CCAPM implied a much lower level of equity returns than empirically observed —an antecedent to Mehra and Prescott (1985) subsequent analysis of the equity premium puzzle.

In short, the CCAPM states returns are predictable if investors are risk averse and are able to anticipate variations in consumption. However, for this theory to be testable it required to solve some obstacles (e.g., nonlinearity, specifying a stochastic process for consumption, etc.). Hansen and Singleton (1983) tried a first approach by developing a log-linear version of the CCAPM. The model was strongly rejected to explain returns on individual stocks and bonds. This result was against the rationalist view, but it was not clear whether the rejection was due to the linearization and other assumptions implied by the model. Then, the GMM (Hansen, 1982) provided a plausible approach for estimating nonlinear systems. Hansen and Singleton (1982) were the first to test CCAPM using GMM: they rejected the model with findings in line with the excess-volatility of Grossman and Shiller (1981). This refuted the simple version of CCAPM, leading to further research to propose enhanced versions of it.

One aspect that would help to develop an enhanced CCAPM was to define the properties that the stochastic discount factor should feature. Hansen and Jagannathan (1991) show that the Sharpe ratio —the ratio of the asset expected excess return over the risk-free rate to the standard deviation of the excess return— gives a lower bound to the volatility of the discount factor. Specifically,

$$\frac{\sigma(d_{t+1})}{E(d_{t+1})} \geq \frac{E(ER_{t+1})}{\sigma(ER_{t+1})} \tag{2.9}$$

where the left-hand side is the ratio of the standard deviation of the discount factor to its expected value and the right-hand side is the Sharpe ratio. The Hansen–Jagannathan bound gives us a clue of why consumption-based models such as the CCAPM are not able to explain the excess volatility of markets: the observed Sharpe ratios imply that the volatility of the discount factor has to be very high,[50] but a low

[50] For the postwar U.S. stock market, The Sharpe ratio for the U.S. stock market is about 0.50. This implies the annualized standard deviation of the discount factor has to be at least 50%, which is really high given that the mean of the discount factor should be close to one (Nobel Prize, 2013).

volatility of consumption and a realistic level of risk aversion imply a much lower volatility of the stochastic discount factor according to CCAPM.

Hansen's method has been useful, nonetheless, to show investors' appetite for risk and their expectations for future returns may vary over time. Since then, some enhanced versions of the CCAPM have had some success in explaining equity premia, volatility and return predictability, although today we cannot find a widely accepted "consensus model" (Nobel Prize, 2013). The behavioral literature, meanwhile, has tried to provide evidence that variations in the discount factor are often not rational. Shefrin (1999), for instance, shows theoretically and empirically that both fundamentals and sentiment affect the risk premium.

2.3. THE TESTABILITY OF THE EMH. CRITIQUES FROM BEHAVIORAL FINANCE

The EMH has been tested, re-formulated and re-tested a myriad of times by an endless number of researchers. However, there is still no consensus among academics about whether financial markets are efficient or not. Moreover, despite the many advances in statistics, databases and theoretical models, it seems that the main outcome has been a clash between the proponents on each side (Lo and MacKinlay, 2001). Much of this disagreement comes from three sources. First, the two alternative definitions of the EMH were used with the rationalist interpretation that they were equivalent, when they were not. Indeed, the confusion of both definitions and the misinterpretation of the behaviorist view on this regard has only added more noise to the debate.

Second, as rationalists have eventually subscribed to the view that former anomalies like return predictability and excess volatility may be explained under a rational approach, the differences between rationalists and behaviorists have eventually become a debate on topics for which either there is mixed evidence or are hard to test in a complex environment such as financial markets. These include whether investors are boundedly rational or not, whether biases are the exception or the rule, whether these biases propagate among investors, whether they have consequences on prices, etc. Finally, a third source of a lack of consensus is the fact that, eventually, the EMH is not a well-defined and empirically refutable hypothesis by itself. The joint hypothesis problem was already highlighted by Fama in his original formulation of EMH (Fama, 1970): the theory is only testable by posing additional assumptions on how asset prices are formed. Then, there is no way to disentangle whether a particular test is rejecting the efficient market hypothesis or any of the additional assumptions.

This section is devoted to provide deeper insight on these and other critiques that have been exposed, mostly by behaviorist researchers, in regard of the testability of the EMH. These include the confusion of the two alternative definitions of the EMH, the joint hypothesis problem, some theoretical and empirical approaches behavioral finance has provided to defy the efficient markets hypothesis, and the alternative interpretation of how markets operate according to behaviorists. They are analyzed next.

2.3.1. Two alternative definitions of EMH

As we saw in Section 2.2, there are two alternative definitions of EMH. The original interpretation defines efficient markets as those where prices fully reflect available information. This responds to the primary reason why we need markets to be efficient: financial markets allocate the economy's capital stock, and for such purpose we require a pricing mechanism that provides firms and investors with unbiased estimations of the fundamental value of such capital stock. A second definition of EMH came in consequence: a market is efficient if it is impossible to make economic profits, in the sense of risk-adjusted returns net of all costs, by trading on the basis of information available. The former definition says security prices are rational, in the sense that they reflect only fundamental characteristics such as risk, but not psychological —such as sentiment (Statman, 1999). The latter says 'there is no free lunch': investors cannot systematically beat the market. The rational-prices interpretation provides support to the economic role of financial markets; the unpredictability-of-markets interpretation provides a testable means to accept or reject the efficiency hypothesis.

However, the original and alternative definitions of market efficiency are not equivalent. This critique could be traced back to Shiller (1984), when he says *"one form of argument (regarding market efficiency) claims that because real returns are nearly unforecastable, the real price of stocks is close to the intrinsic value, that is, the present value with constant discount rate of optimally forecasted future real dividends. This argument for the efficient market hypothesis represents one of the most remarkable errors in the history of economic thought"* (p. 459). Saying 'it is sunny in Australia' does not imply that the logic 'it is sunny, hence we are in Australia' holds. Unpredictability would not be a sufficient condition for market prices to be rational (Soufian, Forbes and Hudson, 2012).

Moreover, trading by irrational investors should make prices excessively volatile too, making price patterns to resemble a random walk in the short term (Shiller, 1984). Shiller and Perron (1985) and Summers (1986) would later formally develop the argument that the power of short-run predictability tests is likely to be very low. In particular, Summers (1986) examines the power of statistical tests used to evaluate the efficiency of speculative markets, and demonstrates they are unable to reject the hypothesis tested, which makes them not useful to claim evidence in favor of market efficiency. To illustrate, in order to have a 50% chance of rejecting the null hypothesis, it would be necessary to have data for over 5.000 years. Poterba and Summers (1988) find similar results.

In addition, the implicit link between the EMH and the random walk hypothesis is incorrect (Lo and MacKinlay, 2001). The reason is the required trade-off between risk and expected return. A positive change in the expected price of an asset may only be the premium required to persuade risk-averse investors to buy the asset and bear the risks. Thus, unpredictability is neither a necessary nor a sufficient condition for rationally determined prices: unpredictable prices do not imply markets are efficient, and the evidence of price predictability does not imply inefficiency. Only under specific assumptions such as risk neutrality they are equivalent. LeRoy (1973) and Lucas (1978) construct explicit examples of well-functioning markets in which the EMH holds but returns are not completely random. LeRoy (1973) shows that, if an investor is sufficiently risk averse as to be willing to avoid holding a security which has unforecastable returns, the random walk hypothesis and the martingale model need not to be satisfied even if markets are informationally efficient. To show it, LeRoy develops a multiperiod capital market model whose main result is that successive rates of return might be positively or negatively correlated depending on how expectations and the variance of the next-period return depend on past earnings.

Meanwhile, Lucas (1978) shows rational asset prices may have a forecastable element that is related to the forecastability of consumption. He develops a model to examine the conditions under which a price series that does not possess the Martingale property would be an evidence of irrational behavior. He suggests that rational expectations as in Muth (1961) is not a description of how agents in the economy behave, but a property likely to be possessed by the *outcome* of the agents' (unspecified) process of learning and adapting. Hence, a good complement to the rational expectations hypothesis would be some form of *stability theory* that explains which forces move an economy toward equilibrium. These ideas were the basis of the eventual adoption of the price forecastability evidence by the rationalist school of thought.

In face of this evidence, behaviorists like Statman (1999) plead for an *engagement* of rational and behavioral researchers: *"finance scholars and professionals would do well to accept market efficiency in the beat-the-market sense but reject in the rational-prices sense"* (p. 18). This would allow finance researchers to stop fighting the *market efficiency battle*, and start exploring asset-pricing models that reflect both psychological and fundamental characteristics. The behavioral finance asserts that some free lunch may appear randomly: occasional excess profit opportunities are required for efficiency to be satisfied (Grossman and Stiglitz, 1980). However, these profits would depend on the ability to obtain some competitive advantage that need not to be regarded as a market inefficiency, but as a fair reward to breakthroughs in financial technology.[51]

Thus, just like in the efficient markets interpretation, most behaviorist researchers accept that no investors will be able to earn excess profits systematically. First, in financial markets barriers to entry are lower and the degree of competition much higher, which makes the average life of excess profitability of financial innovation much smaller (Lo and MacKinlay, 2001). But, moreover, there is no free lunch —particularly in a behaviorist world— because an investor trying to beat the market should

[51] Lo and MacKinlay (2001) provide an interesting metaphor: If the market for biotechnology would be required to be efficient in the EMH sense, a vaccine for the AIDS virus can never be developed —if it could, someone would have already done it!

be able to identify at any given point in time (i) whether stock prices represent fundamental values and, if they do not, (ii) whether irrationality will continue or revert. *Markets can remain irrational a lot longer than you and I can remain solvent* —once said John M. Keynes.

In their battle against the standard finance interpretation that markets are unbeatable, many investment professionals have embraced behavioral finance as an ally (Statman, 1999). However, that is not what behaviorists suggest. In the new paradigm behavioral finance is suggesting, investment professionals will concentrate on investment counseling (Ellis, 1998) rather than market beating. For such purpose, investment professionals should overcome their reluctance to mix the utilitarian features of investments, such as risk, with value-expressive characteristics. The behavioral asset pricing model, BAPM (Shefrin and Statman, 1994), and the behavioral portfolio theory, BPT (Shefrin and Statman, 2000) would be the first efforts in a series of models in such direction.

2.3.2. The joint hypothesis problem

One of the reasons why rationalists and behaviorists seem to have reached a dead end street is the fact that the EMH, by itself, is not a well-defined and empirically refutable hypothesis. Fama himself noticed the joint hypothesis problem: the theory of efficient markets is concerned with whether prices fully reflect available information, but the theory only has empirical content within the context of a more specified model of market equilibrium (Fama, 1970). We need an asset pricing model that guarantees prices reflect all information available, but that, in turn, would impose market efficiency as a *sine qua non* condition.

"This is the price we have to pay to give the theory of efficient markets empirical content" (p. 384): we must specify some auxiliary hypotheses, but then a test of the EMH becomes a test of the auxiliary hypotheses as well. This fact restricts any empirical tests of market efficiency: if it is accepted, it validates both the hypotheses of the model as well as the market efficiency; however, if it is rejected, does it mean markets are inefficient, the asset pricing model is incorrect, or some assumptions (risk aversion, the stochastic process of consumption, dividend smoothing…) are wrong? Moreover, any new statistical tests designed to provide additional insight will require further auxiliary hypotheses which, in turn, may be questioned (Lo and MacKinlay, 2001).

Shleifer (2000) acknowledges that this *"dependence of most tests of market efficiency on a model of risk and expected return is Fama's (1970) deepest insight"* (p. 6). However, the problem of joint testing also makes the market efficiency battle futile (Statman, 1999). No matter how many anomalies are found against the EMH, rationalists may always regard market efficiency as a fact, and move a step forward to modify the last version of the asset pricing models or to suggest a rational interpretation for any new anomaly identified. Furthermore, since the joint hypotheses problem seems to have no solution ahead, the possibility that rationalists and behaviorists ever come to an agreement seems hopeless. Thus, the behavioral finance has had to look for alternative approaches to test the EMH. We analyze them next.

2.3.3. Alternative approaches to question the EMH

In this subsection we introduce several approaches that were suggested to dispute the validity of the EMH. Some of them are theoretical arguments, some are empirically testable approaches. Some were previously mentioned or described along this thesis (e.g., the excess volatility puzzle) while others are first mentioned now, but this is a good opportunity to feature them all together. We have assembled them in three categories: tests for relative efficiency, a stepwise approach, and experimental research. They follow in order.

Tests for relative efficiency

In his address for more cooperation between the fields of economics and finance, Summers (1985) made a fierce critique of the recent developments in the discipline of finance. Many results in finance are based on the pillars of market efficiency (Fama, 1970) and arbitrage principles (Modigliani and Miller, 1958), including the option pricing theory (Black and Scholes, 1973; Merton, 1973a) and the arbitrage pricing theory, APT (Ross, 1976) among others. However, Summers (1985) claims these results only make financial economists comparable with researchers on *ketchup economics*: *"they have shown that two quart bottles of ketchup invariably sells for twice as much as one quart bottles of ketchup, except for deviations traceable to transaction costs"* (p. 634). They reject any analysis based on accounting information, costs of production, wages, consumer incomes and any other factor that might determine the fundamental determinants of prices and, instead, consider prices as the only data worth studying. The evidence that one cannot get a bargain on ketchup makes them claim the efficiency of the ketchup market is the best established fact in empirical economics.

Ketchup economics would show financial economists are only concerned with the inter-relationships among the prices of different financial assets, but they ignore the more important question of what determines the overall level of asset prices. The 'law of one price', that is, the rule that identical goods must have identical prices in different markets (Lamont and Thaler, 2003), ensures relative efficiency, not absolute. The fact that two quart bottles of ketchup sell for twice as much as one quart does not say anything about whether the price of a bottle of ketchup is an efficient estimation of its true value. This way, Summers' interpretation provides behaviorists with a theoretical device symmetrical to that of the joint hypothesis for rationalists. On one hand, the metaphor by Summers (1985) evidences that the law of one price does not imply markets are efficient in absolute terms. On the other, testing the law of one price and rejecting it implies an irrefutable evidence that the price is biased in at least one of the markets and, in consequence, markets are inefficient. Indeed, economic theory requires the law should hold in competitive markets with negligible transaction costs and no barriers to trade.

The good point about relative efficiency is that it can be measured: the average discounts of two different prices for a similar asset can be used for such purpose. This way, several anomalies of the EMH in relative terms have been identified. These include the closed-end fund puzzle, twin stocks, corporate spin-offs, and the forward premium puzzle, among others. Closed-end equity funds are similar to mutual funds, but they are traded in markets: investors cannot redeem their fund shares for cash but they have to sell their shares in the market instead (Lee, Shleifer and Thaler, 1991). The so-called *closed-end fund puzzle*, originally discovered by Zweig (1973), is the empirical evidence that these funds often trade at prices not equal to the per share market value of their underlying stock portfolio. Both discounts and premia of greater than 30 percent are commonly observed (Lamont and Thaler, 2003). Lee et al. (1991) argue that fluctuations in discounts of closed-end funds are driven by irrational investor sentiment and correlated with returns on small stocks. Baker and Wurgler (2007) show that a sentiment index, which includes closed-end fund discounts, is highly correlated with aggregate stock returns.

Twin stocks or Siamese Twins are stocks traded in more than one location. A classic example is Royal Dutch/Shell, which has Royal Dutch shares traded in Amsterdam and Shell shares traded in London. The merger agreement of 1907 states that all cash flows are split 60% for Royal Dutch shares and 40% Shell shares, hence the ratio of their market values should be 1.5. However, this ratio has varied from discounts of 30% in 1981 (Rosenthal and Young, 1990) to premia over 15% in 1996 (Lamont and Thaler, 2003). Froot and Dabora (1999) and Wurgler and Zhuravskaya (2002) show that the relative price of twin stocks is highly correlated with the indexes of the countries where the stocks are traded most actively, suggesting prices are driven by local investor sentiment. A similar situation where the price of two stocks is bounded by a common ratio are in corporate spin-offs. Mitchell, Pulvino and Stafford (2002) and Lamont and Thaler (2003) report examples of how the irrationally high valuation of the spun-off company imply that the parent's *stub value*, i.e., the value of the parent's remaining assets, was negative. A possible explanation is that short-sale constraints and the fact that mispricing often deepens in the short run before it disappears imply limits of arbitrage for risk averse arbitrageurs (DeLong et al., 1990a). Finally, the forward premium is defined as the difference between the forward and spot exchange rates in forex markets. The forward premium puzzle is the empirical evidence that the forward premium forecasts subsequent exchange rate changes (Froot and Thaler, 1990; Burnside et al., 2011), in contradiction with rational expectations models. Froot and Thaler (1990) suggest the bias is due to expectation errors, not to time-varying rational premia for systematic risk, as Fama (1984) suggests. Burnside et al. (2011) offer an alternative explanation based on investors' overconfidence.[52]

[52] Other examples of empirical refutation of the law of one price are in order. First, the index inclusion effect (Shleifer, 1986): the price of a stock tends to increase following the listing announcement. Second, the pricing of American Depositary Receipts (shares of foreign securities traded in U.S. markets): like closed-end funds, ADRs may have prices different from the value of the underlying portfolio (Lamont and Thaler, 2003). Third, short-sale constraints are possible explanations to the evidence that hedge funds preferred to buy tech stocks and ride the dot-com bubble rather than shorting them (Brunnermeier and Nagel, 2004) or that the pricing of Chinese warrants in the late 2000s traded far above their fundamental value (Xiong and Yu, 2011).

In most cases, short sale constraints and other limits to the forces of arbitrage are the alleged causes of these anomalies of the law of one price. Defining arbitrage as the simultaneous buying and selling of the same security for different prices, the absence of arbitrage opportunities is a pillar in modern finance, and should ensure relative efficiency is satisfied. In consequence, when violations of the law of one price are observed, this must be ascribed to two factors (Lamont and Thaler, 2003). First, bounded rationality by some investors make them interpret there are real differences between the two identical assets. Second, some limits to arbitrage must exist for rational arbitrageurs not restoring the equilibrium of prices between both markets. This explanation would lead Shleifer (2000) to summarize the way behavioral finance challenges EMH through the 3-step process that is described below.

A stepwise approach

Shleifer (2000) identifies that the EMH rests on three arguments that rely on progressively weaker assumptions: first, investors are rational, so they value securities rationally; second, to the extent that some investors are not rational, their trades are random, cancelling each other out without affecting prices; and third, to the extent that noise traders are irrational in similar ways, they are met at the market by rational arbitrageurs who eliminate their influence on prices. This interpretation leads Shleifer (2000) to summarize a 3-step process to determine whether efficiency holds in a market or not. Firstly, we determine whether market participants are fully rational. All the beliefs that, based on heuristics rather than rationality, could influence people's behavior are known as *investor sentiment*. Secondly, we analyze whether this sentiment may exhibit trends, rather than generating random trades that cancel each other out. Thirdly, if investors' trades are correlated, how does these inefficiencies survive to price corrections by rational arbitrageurs? That is, could we identify the limits of arbitrage?

This stepwise procedure provides a framework to test informational efficiency in financial markets, considering the elements that might challenge it: market sentiment (behavioral biases leading to market anomalies) and limited arbitrage. The behavioral finance has shown the pervasiveness of these elements in financial markets. First, biases in decision making identified include, among many others, heuristics such as representativeness (Kahneman and Tversky, 1972), judgmental biases such as overconfidence (Oskamp, 1965; Moore and Healy, 2008), theories of choice alternative to expected utility theory such as prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and the effects of framing (Tversky and Kahneman, 1981), and social factors such as social contagion (Asch, 1952; Shiller, 1984). Second, among the reasons suggested to explain a correlated behavior we may include a social behavior by amateur investors (Shiller, 1984) and professional managers (Lakonishok et al., 1992), inducing a market sentiment that contradicts the EMH in instances such as the excess volatility (Shiller, 1981), return predictability (Keim and Stambaugh, 1986; Banz, 1981), herding (Scharfstein and Stein, 1990), overreaction (De Bondt and Thaler, 1985), momentum (Jegadeesh and Titman, 1993), and the equity premium puzzle (Mehra and Prescott, 1985). Finally, some limits of arbitrage in financial markets were identified. Shleifer and Vishny (1997) provide the most extensive analysis. According to them, arbitrage would be risky and limited for several reasons: close substitutes are often not available; fundamental risk is large because mispricing can go worse before it disappears; risk-averse arbitrageurs would have limited interest in risk arbitrage; and agency problems that arise when arbitrageurs manage capital of outside investors.

The limits of arbitrage have been determinant for behavioral finance to contradict the postulates of market efficiency. In short, the EMH as it is interpreted today struggles between two choices: refuting excess volatility (Shiller, 1981) and refuting limits to arbitrage (Shleifer and Vishny, 1997). Refuting both, simultaneously, seems not to be possible. To refute excess volatility, the EMH needs that changes in prices are justified by changes in investors' risk appetite, but this is the same as accepting arbitrage is risky. The original interpretation of a rational arbitrageur now does not make sense: arbitrageurs should be able to (i) correctly interpret fundamentals and (ii) correctly anticipate investors' changes in risk appetite —otherwise their efforts to correct mispricing might be offset by changes in risk appetite in the contrary direction. The analysis of behavioral biases, market anomalies and limits of arbitrage represents the bulk of the behavioral literature. Moreover, this stepwise procedure summarized by Shleifer (2000) is perhaps the best tool behaviorists have to test the validity of the efficient market hypothesis in absolute terms —although their conclusions will always be limited by the joint hypothesis problem. The study of the different behavioral biases and market anomalies identified in the literature, as well as a closer insight on the limits of arbitrage, will be provided in Chapter 4.

Experimental research

A third approach to test the EMH is the use of experimental research. Controlled experiments may be of two types, laboratory and field experiments. Three elements any of them must incorporate are an environment defining the payoffs, an institution defining language and rules, and the participants' behavior (Smith, 2001). Laboratory experiments are randomized experiments that employ a standard subject pool of students, an abstract framing, and an imposed set of rules (Harrison and List, 2004), and which consist of three main factors; experimental manipulation, standardization and random allocation of the sample (Howitt and Cramer, 2008). Field experiments are divided into three categories (Harrison and List, 2004): artefactual, framed and natural. Natural field experiments take place in the participant's natural environment, while artefactual and framed field both mimic a lab experiment and use non-standard subjects. Framed field experiments, in addition, incorporate important elements of the naturally occurring environment (Harrison and List, 2004; Levitt and List, 2009).

Natural field experiments, as they take place in the natural environment, are easier to generalize, but have a problem in regards to their internal validity: researchers have less control over the variables in the experiment. The problem for laboratory and framed field experiments, instead, is in regards of their external validity: the fact that individuals are in an environment where they are aware that their behavior is being monitored, recorded, and subsequently scrutinized, might cause generalizability to be compromised (Levitt and List, 2007). Framed field experiments have the advantage of avoiding some shortcomings of social experiments such as randomization bias, attrition bias and substitution bias (Levitt and List, 2009). The incorporation of markets, repetition and monetary incentives improve their validity, but perhaps not completely solve the problem (Loewenstein, 1999).

The experimental research has revealed helpful to behaviorists because controlled laboratory experimentation helps to go beyond correlational analysis to provide insights on causation (List, 2009), and it revealed a good method to understand human behavior (Levitt and List, 2009). In consequence, the success of experimental economics is particularly relevant in behavioral economics and finance. Only for illustrative purposes, some relevant examples follow: Asch (1952) on social contagion; Milgram's experiments on obedience to authority (Milgram, 1963, 1974); Tversky and Kahneman (1973, 1982a) on representativeness; Kahneman and Tversky (1979) and Tversky and Kahneman (1992) on prospect theory; Knetsch and Sinden (1984) and Samuelson and Zeckhauser (1988) on the status quo bias; Novemsky and Kahneman (2005) on loss aversion; Fischhoff, Slovic and Lichtenstein (1977), Camerer and Lovallo (2004) and Biais et al. (2005) on overconfidence; Lo, Repin and Steenbarger (2005) on emotional responses to trading, etc.

Finally, a relevant area in experimental research to test the EMH is the replication of bubbles. The classic article is Smith, Suchanek and Williams (1988), whose methodology was groundbreaking in the sense that it solved the main drawback of empirical studies that tested the EMH: the fundamentals are unobservable in empirical studies, while they become perfectly observable in laboratory asset markets. Additional experimental research on asset bubbles include Porter and Smith (1995), Dufwenberg, Lindqvist and Moore (2005) and Lei and Vesely (2009), among many others. Further description of asset bubbles was provided in Chapter 1, while for further review on experimental markets we recommend Cason and Noussair (2001) and Plott and Smith (2008).

2.3.4. Adaptive market hypothesis: An alternative theory to EMH

This fourth subsection, rather than a critique to the testability of the EMH, provides an alternative interpretation to how markets work: the Adaptive Market Hypothesis, AMH (Lo, 2004). The AMH seeks to reconcile the EMH and its critics through an evolutionary approach to economic interactions. The key point is what Andrew Lo names the *sociology of market efficiency*: economic systems involve human interactions, much complex than the interactions in physical sciences; in consequence, a purely deductive approach as in modern physics may not always be appropriate for economic analysis. Instead, the AMH can be viewed as a new version of the EMH, derived from evolutionary principles: financial markets would be ecological systems in which different *species* (different groups of market participants) compete for scarce resources. Financial markets would be neither efficient nor irrational, but some combination of both: *"prices reflect as much information as dictated by the combination of environmental* *conditions and the number and nature of "species" in the economy or, to use a more appropriate biological term, the ecology"* (p. 23). The dynamics of evolution (i.e., competition, mutation, reproduction, and natural selection) determine market efficiency and the profitability of the investment strategies.

The evolutionary framework in AMH helps to reconcile the contradictions between EMH and the behavioral literature at least in two instances. First, Simon's (1955, 1959) notions of bounded rationality and satisficing —as an alternative to optimization— were dismissed by rationalists because of one specific criticism: what determines the point at which an individual stops optimizing and reaches a satisfactory solution? The evolutionary perspective in AMH provides the answer: it is determined not analytically, but through trial and error and natural selection. The heuristics investors use may work in a specific environment, but if it changes, they will fail. In such cases, we observe behavioral biases, but rather than being an irrational behavior, it would be evidence of a 'maladaptive' behavior. Second, Grossman and Stiglitz's impossibility of informationally efficient markets (Grossman and Stiglitz, 1980) highlighted the paradox of efficient markets: if all investors believe markets are efficient, markets will be inefficient because there would be no investors willing to spend resources on fundamental analysis. The AMH, instead, considers profit opportunities do exist in financial markets. However, they disappear as they are exploited, while new opportunities are also constantly being created.[53]

Finally, the AMH better responds to some critiques that were posed to EMH. A first example is that the EMH postulates markets are always efficient while behaviorists, on the contrary, do not say markets are always irrational: they simply may go irrational sometimes. However, rationalists may argue as well this may be interpreted as the EMH being the paradigm by default, and behavioral biases the exception. The AMH, with its suggestion that markets are neither efficient nor irrational, but some combination of both, meets the best of both views. The second example is a classic one. The EMH implies that active portfolio management is useless. Hence, the popularity of active management among investors would imply a market failure: informational efficiency leads to economic inefficiency in the financial industry. Fama himself declares to find it completely puzzling why investors still entrust around 80% of the money in mutual funds to active managers.[54] The AMH, instead, considers that profit opportunities do exist, investors compete to exploit them, and the best way to approach markets is to adapt to changing market conditions.

---

[53] Lo (2004) sets several implications. First, the risk-return tradeoff is unlikely to be stable over time. Instead, market ecology and changes in institutional aspects such as the regulatory environment and tax laws would determine how it evolves. Second, arbitrage opportunities do arise from time to time —otherwise there would be no incentive to gather information, and the price discovery aspect of financial markets would collapse. Third, the profitability of investment and trading strategies will also wax and wane. Fourth, while profit and utility maximization are relevant aspects of market ecology, what determines the evolution of markets —and, in consequence, is the only objective that matters— is survival. Fifth, innovation is the key to survival: *"The classic EMH suggests that certain levels of expected returns can be achieved simply by bearing a sufficient degree of risk. The AMH implies that because the risk/reward relation varies through time, a better way to achieve a consistent level of expected returns is to adapt to changing market conditions"* (p. 25).

[54] Here we quote an interview at CNN Money, available from http://money.cnn.com/2013/12/06/investing/eugene-fama-markets.pr.fortune/

2.4. EMPIRICAL TESTS OF THE EMH. A SHORT REVIEW

Although the testability of the EMH has been put under question, as we summarized in Section 2.3, a myriad of empirical tests of the weak, semi-strong and strong form of the EMH that have been performed. In this section we make a brief review which, nonetheless, is not intended to be exhaustive. On one hand, the number of articles published in the last fifty years is immeasurable. On the other, a detailed analysis of all the approaches available to test the different degrees of market efficiency is beyond the scope of this thesis. For a deeper insight on the tests and a more extensive list of research articles, we recommend some of the authors we have followed to compose this taxonomy. These include Campbell, Lo and MacKinlay (1996), Fama (1970, 1991), Lo (1997), Nobel Prize (2013) and Ruiz (2005).

The taxonomy basically follows Fama (1970), but with some amendments. In his first suggestion, weak form tests were concerned with the forecast power of past returns ('how well do past returns predict future returns'), semi-strong tests with how quickly security prices adjust to public information announcements (denoted *event studies* in Fama 1991) and strong form tests with private information that is not fully reflected in market prices ('tests for private information' in Fama 1991). The main change is the category we include the literature on tests of return predictability —both time series and cross section. Fama (1991), for instance, changes the categories in Fama (1970) to make the first one cover the broader topic of tests for return predictability rather than only tests for the forecast power of past returns. However, two criticisms can be made to this interpretation. First, some of these tests may be regarded as either test of the weak form or the semi-strong form. Take for instance the tests for overreaction and the contrary investing strategy versus underreaction and the momentum strategy. We may interpret them as tracing whether past performance helps to predict future price movements, but we may also interpret them as an evidence of markets not properly adjusting information into prices, either going too far (overreaction) or being too slow to reflect fundamentals (underreaction). Second, some other tests simply fit better in the second category. For instance, volatility tests analyze the excess volatility of prices to reflect the fundamentals, while tests of herd behavior seek to trace evidence of whether investors follow other investors' decisions rather than fundamentals.

In consequence, the taxonomy that follows below considers the following distribution. Tests of the weak form EMH are concerned with the forecast power of past returns. These include tests of the random walk hypothesis that may take the form of tests for serial correlation, runs tests, and filter tests. Besides, the classic tests for calendar effects are also included: they are used to determine whether non informative data (like the month or the day of the week) is helpful to predict future price performance. Tests of the semi-strong form EMH are concerned with the estimation of abnormal returns. These include time series analyses of public information, cross section analyses of public information, and event studies. Finally, tests of the strong form EMH analyze the ability that corporate insiders and other groups of professional investors may have to obtain excess profits, which would evidence they are making use of private information that is not fully reflected in prices.

2.4.1. Weak form EMH tests

Tests of the weak form EMH are concerned with the forecast power of past returns. Following Fama (1965b), tests of the random walk hypothesis may take the form of tests for serial correlation, runs tests, and filter tests. Besides, following Fama (1991), tests of the weak-form EMH would also include calendar effects. The taxonomy is summarized in Table 2.1.

TABLE 2.1 – Tests of the weak form EMH

Tests of weak form EMH		
Type of Test	**Evidence in favour EMH**	**Evidence against EMH**
I.- Tests of statistical independence of prices / returns		
a) Serial correlation		
▪ Autocorrelation	Kadel (1953), Fama (1965b)	Poterba and Summers (1988)
▪ Non-linear stochastic processes		Taylor (1982)
b) Runs tests	Fama (1965)	
II.- Tests of trading rules		
c) Filter rules	Alexander (1961), Fama (1965b), Curcio et al. (1997)	Conrad and Kaul (1998)
III.- Tests for seasonality of returns		
d) Calendar effects		
January effect	Gaunt et al. (2000), Gu (2003)	Officer (1975), Keim (1983), Grinblatt and Keloharju (2004)
Monday effect		Jaffe and Westerfield (1985), Berument and Kiymaz (2001)

Source: Own elaboration

Tests of statistical independence of prices or returns trace evidence of short term predictability (within days or weeks) due to statistical correlation between consecutive prices or returns. This type of tests are divided in two categories: serial correlation and runs tests. Early serial correlation tests that support the independence assumption include Kendall (1953), Osborne (1959), Cootner (1962), Fama (1965b), Samuelson (1965), Fama and Blume (1966) and Mandelbrot (1966). Methods of spectral analysis such as Granger and Morgenstern (1963) and Godfrey, Granger and Morgenstern (1964) yield similar results. Literature in the 70s and 80s finds a serial correlation of short-term returns, but agreeing that predictability would be small in magnitude. These include Keim (1986), French and Roll (1986), Lo and MacKinlay (1988), Poterba and Summers (1988) and Fama and French (1988b). However, all these autocorrelation and spectral tests assume returns are generated by a linear stochastic process, an assumption Taylor (1982a) shows to be assumption. Hence, several authors have modeled non-linear stochastic process using models of conditional variance such as ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) —recent articles are Bekaert and Harvey (1997) and Andersen et al. (2003). Others have followed chaos theory (Eckmann and Ruelle, 1985), including Hinich and Patterson (1985, 1989) and Brock and Hommes (1998). Recent papers for this line of research on nonlinearity and autoregressive models include Shively (2003) and Narayan (2006), among others. Finally, runs tests are another means to test the statistical independence of prices. Introduced by Fama (1965b), the approach determines the randomness of a price series by analyzing whether a run of successive price changes of the same sign happen more frequently than could be as a result of chance. Recent examples are El-Erian and Kumar (1995), Hassan, Haque and Lawrence (2006) and Worthington and Higgs (2009).

A second type of tests of the weak form EMH are trading tests or tests of trading rules. The early approach was again settled by Fama (1965b), who notices that if the random walk hypothesis holds, no trading rules should give excess profits above a buy-and-hold strategy. Thus, we may test the actual profitability of any given trading rule. Since Fama (1965b) tested Alexander's filter rule in particular (Alexander, 1961), this type of tests are often named filter rule tests. Fama and Blume (1966) show that any potential profits of these filter rules were exceeded by trading costs. Later research traced some profitability, such as Conrad and Kaul (1998) and Neely and Weller (1999). Results are mixed, however, when it comes to compare potential profits and transaction costs: some suggest they are not profitable (e.g., Curcio et al., 1997), others suggest they are so (e.g., Cooper, 1999).

Finally, a third type are the tests for calendar effects or seasonality of returns, which pioneered the research on market efficiency, as early works go back to Wachtel (1942) and Osborne (1962), while the January effect (Wachtel, 1942; Officer, 1975) was already a classic when Shiller uncovered the excess volatility. These tests search for whatever patterns of seasonality in prices or returns, but two classics are the day-of-the-week effect and the January effect. The latter was described as the most mystifying seasonal (Fama, 1991). Officer (1975) detected that Australian stock returns, particularly on small cap stocks, were on average higher in January than in any other month. Rozeff and Kinney (1976) traced the same evidence on the NYSE, and similar results were replicated in different markets and periods since then. Keim (1983), in particular, shows the January effect is basically a size effect as in Banz (1981). The day-of-the-week effect, instead, seeks for return patterns for different days of the week. A classic result is the Monday effect: several authors (e.g., Cross, 1973; French, 1980; Jaffe and Westerfield, 1985) noted that Monday returns are on average lower than on other days. Other traced regularities are the weekend effect, holiday effect, end-of-month, turn-of-the-year and Tuesday effect —perhaps a delayed Monday effect caused by the different trading hours worldwide (Keim, 1983; Martikainen and Puttonen, 1996).

Some rational interpretations have been suggested for these seasonal effects. Thus, the January effect has been attributed to tax effects since Watchel (1942) —investors sell losers in December to avoid paying higher taxes— while the Monday effect is explained in terms of market microstructure —returns deviate from average daily returns by less than the bid-ask spread (Lakonishok and Smidt, 1988). However, many authors suggest these effects would be only spurious and tend to disappear once they are identified (e.g., Gu, 2003). The debate continues today: Chen and Singal (2004), Grinblatt and Keloharju (2004) and Starks, Yong and Zheng (2006) support the tax-loss selling explanation of the January effect, Gaunt, Gray and Mclvor (2000) reject the January effect, Berument and Kiymaz (2001) verify a Monday effect, and Yuan, Zheng and Zhu (2006) identify a correlation between lunar phases and stock market returns.

To sum up, the prevailing opinion today regarding the weak form EMH is that stock returns are somewhat predictable in the short term, but this forecast power is hardly profitable if transaction costs are considered. Stock markets seem to satisfy the no-arbitrage model with unpredictable forecasting errors in the short term, but this does not impede that long term returns may exhibit considerable predictability (Nobel Prize, 2013).

2.4.2. Semi-strong form EMH tests

Tests of the semi-strong form EMH are concerned with the estimation of abnormal returns. Following the discussion above, we included time series and cross section analysis of public information, as well as the classic event studies considered by Fama (1991). The list is summarized in Table 2.2.

Time series analysis

A relevant field in the literature of market efficiency are the tests for long-term predictability of stock returns. Long-term predictability contradicts the EMH as it suggests markets are not properly incorporating information into prices, but some rational interpretations for these apparent anomalies have also been provided. Indeed, the fact that the joint hypothesis problem is particularly relevant in these type of tests only makes it harder to reach a consensus. The category includes the excess volatility puzzle, tests for mean reversion and predictability of returns, tests for overreaction and the contrary investing strategy, tests for underreaction and momentum strategy, and the research on herd behavior in financial markets. A brief review of each topic follows.

The first volatility tests were devised by Shiller (1979) in bond markets and Shiller (1981) and LeRoy and Porter (1981) in stock markets. They are regarded as the first strong evidence against EMH, as they confirmed markets fluctuate much more than they should if prices only followed fundamentals. Marsh and Merton (1986) and Kleidon (1986) questioned the general validity of these findings as they assumed price stationarity and a constant discount rate over time. The critique on stationarity of prices was later solved by Campbell and Shiller (1987), who use the recently developed theory of cointegrated processes (Engle and Granger, 1987) to model dividends and stock prices in a more general way. The second critique, regarding the discount factor to be used, was tackled by Grossman and Shiller (1981) who made it equal to the intertemporal marginal rate of substitution for consumption only to confirm the excess volatility anomaly was again observed. A classic paper that deserves mention is Roll (1984), who analyzes the orange juice futures market to find that weather surprises only explain a small part of the variability in prices. Other relevant papers during the 80s include Michener (1982), Flavin (1983), Merton (1987a), West (1988a), Campbell (1991) and Barsky and DeLong (1993). Recent examples are Gabaix et al. (2006), Otrok, Ravikumar and Whiteman (2007) and Dumas, Kurshev and Uppal (2009).

TABLE 2.2 – Tests of the semi-strong form EMH

Tests of semi-strong form EMH			
Type of Test	**Items**	**Evidence in favour EMH**	**Evidence against EMH**
I.- Time Series analysis			
a) Long-term return predictability			
■ Volatility tests			Shiller (1979, 1981), Roll (1984)
■ Mean reversion and predictability of returns	Dividend yield (D/P), PER	Ang and Bekaert (2007)	Shiller (1984), Campbell and Yogo (2006)
■ Tests of contrary investing strategy	Overreaction		De Bondt and Thaler (1985), Daniel et al. (1998)
■ Tests of momentum strategy	Underreaction		Jegadeesh and Titman (1993), Chui et al. (2010)
■ Herding			Lakonishok et al. (1992), Jegadeesh and Kim (2010)
b) Predictability in other asset markets			
	Default spread, TS spread	Fama and French (1992)	Campbell and Shiller (1991)
	Foreign Exchange market		Froot and Thaler (1990)
II.- Cross section analysis			
c) Size		Fama and French (1993), Amihud (2002)	Banz (1981)
d) Financial ratios	PER, BV/MV	Fama and French (1992)	Basu (1977), Stattman (1980), Bhandari (1988)
e) Neglected firms		Beard and Sias (1997)	Barber et al. (1993)
III.- Event studies			
f) Announcements			
	Quarterly earnings reports		Ball and Brown (1968), Ball (1992)
	Dividend announcements	Liv et al. (2008)	Charest (1978), Bali (2003)
g) Corporate events	IPOs, M&As Strategic decisions	Brav and Gompers (1997)	Loughran and Ritter (1995)
h) Stock exchanges	Splits Block trades Exchange listings	Fama et al. (1969) Scholes (1972)	Grinblatt et al. (1984)
i) Economic news	Changes in interest rates Accounting changes World and economic news	French et al. (1987)	

Source: Own elaboration

A second field in the literature of long-term predictability is the evidence that financial ratios such as dividend yield and PER are helpful to predict stock returns over time. Since the excess volatility implies returns should be mean reverting, a first focus was set on the predictability of dividend yields. Shiller (1984) finds empirical evidence that high d/P ratios forecast higher returns. Hence, a contrary investing strategy would be profitable by buying when price-to-dividend ratios are low and vice versa. Other variables observed to have a predictable power over returns follow in order. First, excess returns on stocks tend to be negatively correlated with expected inflation (Bodie, 1976) so, in consequence, high short-term interest rates tend to anticipate lower stock-market returns (Fama and Schwert, 1977). Second, Keim and Stambaugh identify credit spreads on bond markets and two constructed variables on stock markets. Third, the term structure of interest rates would predict stock returns (Campbell, 1987). Fourth, a long moving average of real earnings predicts future dividends, and the ratio of such earnings variable to price anticipates future stock returns (Campbell and Shiller, 1988a).[55] The fact that these variables are often correlated with the business cycle would support the rationalist view that return predictability would be a consequence of changes in the discount factor. However, the debate continues. Campbell and Yogo (2006) note that the classic tests of return predictability may be invalid when the predictor variable is persistent and its innovations are highly correlated with returns. They introduce an efficient test of predictability to solve this problem and find evidence of it. Contrariwise, Ang and Bekaert (2007) find no evidence that dividend yields predict excess returns in the long run.

The ability of the contrary investing strategy to outperform is also implicit in the hypothesis that markets overreact. Research in experimental psychology suggests people adopt an internal approach to prediction that is likely to produce underestimation (Kahneman and Tversky, 1982a). Hence, when they revise their beliefs in face of unexpected events, they tend to overweight recent news and underweight prior data. De Bondt and Thaler (1985) used these ideas to introduce the concept of overreaction in stock markets: portfolios of loser stocks —those that have experienced extreme capital losses in the past-outperformed the market by 20% three years after portfolio formation, while winners lose 5%. Similar results, theoretical or empirical, were obtained by Lo and MacKinlay (1990), Chopra, Lakonishok and Ritter (1992), Campbell and Kyle (1993), Daniel, Hirshleifer and Subrahmanyam (1998), Gropp (2004), Peyer and Vermaelen (2009), Diether, Lee and Werner (2009), and Schmeling (2009).[56]

---

[55] This result was later used by Shiller (2000b) to propose his famous Cyclically Adjusted Price-Earnings (CAPE) ratio. Also known as the P/E 10 ratio or the Shiller ratio, it is a refined version of the PER ratio where a 10-year average, inflation-adjusted, estimation of earnings is used to compute the ratio. A similar method to smooth earnings over past years can be traced back to Graham and Dodd (1934).

[56] Some authors provide a rational explanation for periods when a contrary investing strategy yields good results. Chan (1988) suggests that the risk of winners and losers varies over time. This way, losers would have higher betas when they are added to the portfolio because lower prices imply higher indebtedness, hence higher risk. In consequence, the excess returns of losers would not be such thing, but only a fair return for the greater risk assumed. Nonetheless, this interpretation goes against Fama and French (1993)'s finding that the book-to-market ratio captures a risk factor that β does not explain. Conrad and Kaul (1993) suggest that overreaction findings in the literature would be attributable to biases in computed returns when monthly cumulative average returns are used. Loughran and Ritter (1996) dispute this only makes little difference in returns, as Conrad and Kaul (1993) confound cross-sectional patterns and aggregate time-series mean reversion, and introduce a survivor bias.

Then, Jegadeesh and Titman (1993) documented evidence on the opposite direction. Momentum strategies may also work: buying winners and selling losers generate positive returns over 3 to 12 months after portfolio formation, suggesting prices underreact to new information available. The first evidence of market underreaction is the post-earnings announcement drift, by Ball and Brown (1968). Since then, many researchers have found markets underreact, including Bernard and Thomas (1990), Chan, Jegadeesh and Lakonishok (1996), Lee and Swaminathan (2000), Jegadeesh and Titman (2001), Griffin et al. (2003), Grinblatt and Han (2005) and Chui, Titman and Wei (2010). Others argue that the profitability of investing in momentum strategies might be a compensation for bearing asymmetric risks —in particular, the higher exposure to downside risk of some stocks (e.g., Ang, Chen and Xing, 2001).

Thus, there is evidence that markets can overreact as well as underreact, and some theoretical models suggest how overreaction and underreaction may coexist. Relevant examples are Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999). This would contradict the original EMH view that prices fully reflect information, while it satisfies the no free lunch interpretation: otherwise it would require investors to anticipate whether contrarians will beat momentum traders or vice versa. In addition, markets may be even more complex than that: investors, both amateur and professional traders, often mimic other investors' investment decisions —a behavior known as herding. Several empirical tests have confirmed investors do herd, including Lakonishok, Shleifer and Vishny (1992), Wermers (1999), Hwang and Salmon (2004), Jegadeesh and Kim (2010).

All these tests above refer to stock markets, but there is evidence of return predictability in other asset markets, too. Two relevant examples are bond markets and foreign exchange markets. In bond markets, the excess volatility of long-term bonds (Shiller, 1979) implies bond returns are predictable. Several authors (Shiller, Campbell and Schoenholtz, 1983; Fama and Bliss, 1987; Campbell and Shiller, 1991) find the slope of the yield curve has a forecast power. Campbell (1987) and Fama and French (1989) observe that the term structure predicts stock returns as well, and consequently the excess returns on stocks and long-maturity bonds would be correlated. A second predictor in bond markets are default spreads —that is, the difference in returns between corporate bonds and long-term government bonds. Authors that confirm it include Chen, Roll and Ross (1986) and Fama and French (1993). Finally, in foreign exchange markets, strategies such as the currency carry trade —i.e., borrowing low-yielding currencies and lending high-yielding ones— should not yield excess returns, since the uncovered interest rate parity predicts the difference in interest rates will be equivalent to the currency depreciation (Bekaert, Wei and Xing, 2007). However, the forward premium puzzle (e.g., Froot and Thaler, 1990) already described would be an evidence against it.

Cross section analysis

A second type of tests of the semi-strong EMH are those that seek to trace evidence of a long-term predictability of cross-sectional returns. Cross-sectional return predictability would contradict the EMH because it suggests markets are not properly incorporating firms' fundamentals into prices. However, the joint-hypothesis problem introduces the possibility to modify the asset pricing models to account for the anomalies observed. Early tests of the CAPM (Douglas, 1969; Black, Jensen and Scholes, 1972) obtained values for the riskless rate of return that were too high to be acceptable and led to biased inference due to the common strong cross-sectional correlation in stock returns. Then, Fama and MacBeth (1973) provided the famous Fama–MacBeth regressions for parameter estimation: a two-step approach that solves that problem of cross-sectional correlation,[57] and that is today a standard method for testing multi-factor cross-sectional asset pricing models (Nobel Prize, 2013). Now, the ability of the CAPM to explain differences in expected returns across stocks could be tested, and Fama and MacBeth (1973) obtained positive results. However, some empirical contradictions of the Sharpe–Lintner model were finally found, being the most relevant the size effect, leverage risk, and the predictability of financial ratios such as PER and BV/MV (book value to market value). They are analyzed next.

The first observed cross-sectional anomaly was the size effect: small-cap stocks tend to exhibit higher risk-adjusted returns than those predicted by the CAPM (Banz, 1981). Reinganum (1981), Lakonishok and Smidt (1986), and Fama and French (1992, 1993) later confirmed this result. Zarowin (1989, 1990) argues size explains the profitability of contrary investing. More recent papers include Loughran (1997), Barry et al. (2002), Fama and French (2008) and Hou, Karolyi and Kho (2011). Most explanations of this anomaly suggest small firms are exposed to risk factors not recognized in classic asset pricing models. Banz (1981), for instance, follows Klein and Bawa (1977) to suggest it is likely that there is a lack of corporate information for smaller firms. Authors providing empirical evidence of this include Atiase (1985, 1987) and Dempsey (1989), while Barry and Brown (1984) and Merton (1987b) provide two models on a similar basis. Finally, Arbel and Strebel (1982) associate the lack of information to the neglected firms' effect. An alternative risk factor would be a liquidity premium due to a lower trading volume (James and Edmister, 1983). Amihud (2002) supports this view and Roll (1981) suggests that infrequent trading leads to a bias in risk estimation, understating the actual risk from holding a small firm portfolio. This would refute the mere existence of a size effect. However, other authors (e.g., Reinganum, 1982; Keim, 1983) consider this bias too small to explain the anomaly. Eventually, Fama and French (1993) included firm size as a common risk factor in the returns on stocks.

A second group of cross-sectional anomalies include some financial ratios claimed to have some predictive power. The most relevant ratios are PER and its inverse E/P (Basu, 1977, 1983), book value to market value, BV/MV (Stattman, 1980; Rosenberg, Reid and Lanstein, 1985), and financial leverage measured as debt-to-equity ratio (Bhandari, 1988). First, Basu (1977) finds evidence that securities

[57] Noting that lack of predictability and constant expected returns over time imply returns are uncorrelated over time, Fama and MacBeth (1973) suggest a two-step procedure to obtain empirical estimations of the CAPM. The first step estimates a series of cross-sectional regressions of stock returns to obtain the expected returns according to the asset-pricing model. The second step estimates the time-series average of the coefficients from the cross-sectional regressions, in order to test whether the averages deviate from the expected values.

with low PER ratios tend to outperform high P/E stocks, and Basu (1983) extends the evidence to the earnings yield even if experimental control is exercised over differences in firm size. Recent research includes Desai, Rajgopal and Venkatachalam (2004) and Dechow, Ge and Schrand (2010). Second, Stattman (1980) finds a positive relationship between average returns on U.S. stocks and BV/MV, while Rosenberg et al. (1985) show that a book/price strategy that buys stocks with high ratios and sells those with low ones is profitable. Recent research include Chan, Hamao and Lakonishok (1991), Raghavendra and Vermaelen (1998) and Dong et al. (2006). Finally, Bhandari (1988) show that a positive relationship exists between debt-to-equity ratios, D/E, and expected returns. Leverage risk is obviously a factor that should be captured by betas in the CAPM model, but Bhandari finds debt-to-equity ratios are able to explain the cross-section of average stock returns once size and beta have been considered. Recent research includes Penman, Richardson and Tuna (2007) and Gomes and Schmid (2010).

Lastly, another common cross-sectional anomaly is the neglected firms' effect: stocks that are not followed by security analysts tend to outperform the market. This anomaly is easy to interpret under the theory of Grossman and Stiglitz (1980): in markets where analysts choose not to be informed, prices do not fully reveal information and hence profit opportunities may appear. The effect is related to the size bias, since neglected firms are often small firms (Arbel and Strebel, 1982; Arbel, Carvell and Strebel, 1983). Recent papers offer a mixed evidence. On one hand, the number of analysts following the security (Barber, Griffin and Lev, 1993) and the informational deficiency associated to these firms (Downs and Güner, 2000) would be key factors that influence whether excess returns are observed or not. Besides, Hong, Lim and Stein (2000) find the effect greater for stocks that are past losers than for past winners. On the other hand, Beard and Sias (1997) find no evidence of a neglected premium, while Ennis and Sebastian (2002) suggest the small-cap alpha is a myth that stems from tests that ignore management fees, use inappropriate benchmarks, and ignore a survivorship bias (Brown et al., 1992).[58]

Event studies

The third category of tests of the semi-strong form are known as event studies after Fama (1970): the study of how security prices adjust to *"one kind of information generating event (e.g., stock splits, announcements of financial reports by firms, new security issues, etc.)"* (p. 404). The seminal paper is by Fama et al. (1969), who noted that empirical tests at that time tried to *infer* market efficiency from the independence of successive price changes, but this does not say much about the speed of adjustment of prices to new information. In particular, Fama et al. (1969 studied the effect on prices of stock splits,[59] but all event studies follow the same logic. When new information about some significant economic event arrives to the market, there must be an immediate price impact and some unusual behavior in the

[58] The list of anomalies is endless, and so our analysis is obviously not fully comprehensive. As an example, a recurrent anomaly in the literature not included here is the Value Line effect (Copeland and Mayers, 1982; Porras and Griswold, 2000).

[59] However Ball and Brown (1968), another classic in the literature of event studies, was published in 1968, an original version of Fama et al. (1969) was available as a Report No. 6715 of the University of Chicago in 1967.

rates of return at the time of the announcement, and then prices should subsequently remain unpredictable. The difference across the alternative tests available is in regard of the kind of event that is analyzed. Four are the most common categories, which are analyzed in what follows.

The first one considers earnings and dividends announcements. Ball and Brown (1968) analyzed the effect on prices of the release of the income report, to provide empirical evidence that prices not only adjust to new information, but they often anticipate the announcement. However, they also find an apparent anomaly: when firms do not meet their expected profits, prices tend to respond to earnings for about a year after they are announced. Several studies confirmed this post-earnings announcement drift, both for unexpectedly positive or negative profits, including Jones and Litzenberger (1970), Foster, Olsen and Shevlin (1984) and Ball (1992). Recent literature includes Bartov, Radhakrishnan and Krinsky (2000), Mendenhall (2004), Sadka (2005) and DellaVigna and Pollet (2009). They all confirm evidence of the anomaly. In addition, La Porta et al. (1997) relate the observed outperformance of value stocks with this announcement anomaly: earnings surprises are systematically more positive for value stocks.

Rational interpretations of the anomaly include an incorrect measurement of corporate results (Warfield and Wild, 1992) and the existence of different econometric problems (Patel, 1989; Brennan, 1991). In addition, it might be a fair compensation for changes in non-observed risk factors such as liquidity risk (Sadka, 2005). However, Fama (1998) considers it, together with the profitability of momentum strategies, the two anomalies that rationalists are not able to explain. Indeed, the classic interpretation considers it is caused by investors' underreaction to information when it is first released (Bernard and Thomas, 1990), also because they are not aware of the serial correlation in profits (Bernard, 1993) and they underestimate such correlation (Ball and Bartov, 1996). Recent articles (e.g., Mendenhall, 2004; DellaVigna and Pollet, 2009) mostly subscribe to this view. Models that provide a formal approach to this underreaction interpretation include Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999). Similar studies about the effect of dividend announcements on prices include Charest (1978), who obtains empirical evidence that excess returns are observable during two years after a dividend rise is announced and, in the same line, Ball (1978), Roll (1984), Grinblatt, Masulis and Titman (1984) and Michaely, Thaler and Womack (1995). Recent literature, though, offers mixed reviews, including Bali (2003) in favor of the anomaly and Liu, Szewcyk and Zantout (2008) in favor of market efficiency.

The second category of event studies analyzes the effect on prices of corporate events such as IPOs, mergers and acquisitions, and other types of corporate strategic decisions. The most common are the analysis of the announcement of initial public offerings, IPOs, and seasoned equity offerings, SEOs. Asquith and Mullins (1986) find empirical evidence that investors consider SEOs to be bad news, reducing stock prices in consequence. Besides, the *IPOs underpricing puzzle* is the empirical evidence that a large number of initial public offerings have been underpriced by more than 10% (Purnanandam and Swaminathan, 2004) and showed a significant price appreciation during the first days of trading in consequence. Then, after the initial run-up in price, IPOs often become poor long run investments (Loughran and Ritter, 1995). However, recent literature is not so conclusive. For instance, Brav and Gompers (1997) suggest venture-backed companies do not significantly underperform, but the smallest nonventure-backed firms do; Loughran and Ritter (2004) provide evidence that IPO underpricing changes significantly over time; and Purnanandam and Swaminathan (2004) show IPOs may also be significantly overvalued. Recent literature includes Shivakumar (2000) and Cohen and Zarowin (2010) on SEOs, and Ritter and Welch (2002) and Arthurs et al. (2008) on IPOs. Similar studies were performed on mergers and acquisitions (Dennis and McConnell, 1986; Aktas et al., 2007), market share repurchases (Ikenberry, Lakonishok and Vermaelen, 1995; von Eije and Megginson, 2008) and other strategic decisions of firms, such as joint ventures (Park and Dongcheoi, 1997; Hanvanich and Çavusgil, 2001) and others (e.g., Balasubramanian, Matour and Thakur, 2005; Jeong and Stylianou, 2010).

The third category analyzes the potential effect on prices of information about trading in stock exchanges. This includes splits announcements, exchange listings and block trades. The study of stock splits and their effect on prices is a classic since Fama et al. (1969). Grinblatt et al. (1984) show stock prices, on average, react positively to stock split announcements. Similar results were replicated by Asquith, Healy and Palepu (1989) and Ikenberry and Rammath (2002), among others. Ikenberry, Rankine and Stice (1996) suggest splits realign prices to a lower trading range and that the market underreacts to split announcements. However, we may find evidence against this anomaly, too —e.g., Byun and Rozeff (2003). Regarding block trades, Kraus and Stoll (1972b) and Scholes (1972) provided early evidence that prices react efficiently to the information conveyed in the sale of large blocks of shares. Subsequent literature in support of the efficient hypothesis includes Easley and O'Hara (1987) and Fama (1990). The study of price effects following a stock exchange listing announcement —i.e., the inclusion of a given stock in a particular selective or sectorial index— was pioneered by Dharan and Ikenberry (1995). Doidge, Karolyi and Stulz (2004) find that foreign firms listed in the U.S. are valued significantly higher than non-cross-listed firms from the same country. They suggest that a U.S. listing reduces the extent to which controlling shareholders can engage in expropriation, which would increase the firm's ability to take advantage of growth opportunities.

Finally, a fourth category of events are the effects that relevant economic news might have on prices. Examples are the effects of changes in the interest rate over prices (e.g., French, Schwert and Stambaugh, 1987; Bomfim, 2003; and Rigobon and Sack, 2004), the effect on prices of accounting changes (e.g., Nourayi, 1994), changes in reserve requirements of banks (e.g., Kolari, Mahajan and Saunders, 1988) and other normative standards (e.g., McGuire and Dilts, 2008), as well as major economic news (e.g., Conrad et al., 2006).

To sum up, the evidence against EMH for time series studies led to a debate between rationalists and behaviorists about the role of the discount factor. The strong evidence against EMH in cross section led Fama and French (1993) to provide a model that aims to substitute CAPM by accounting for several additional risk factors, both in the stock market (3-factor model) and the bond market. Finally, the vast majority of event studies have supported EMH (Nobel Prize, 2013), with only some exceptions —the most notable, the post earnings announcement drift first documented by Ball and Brown (1968).

2.4.3. Strong form EMH tests

The analysis of the strong form tests the effect of private information not fully reflected in market prices. This is the less analyzed form of efficiency, due to the difficulties implied in its empirical contrast (Del Brío, 2003): we cannot observe either the private information available at the market or what would be the market prices that fully reflect this information. Thus, indirect ways to test it had to be performed, by considering the study of agents which are supposed to have access to inside information, including corporate insiders and different sorts of professional investors. However, these tests are also limited as there is not much data available, neither we will be able to assert when a particular piece of inside information has arrived to the market. Unlike tests of semi-strong EMH, tests of the strong-form EMH analyze market returns *before* a particular announcement in order to trace evidence of insiders making excess profits by making use of such privileged information. Following the discussion above, we have considered to include two types of tests: those that focus on corporate insiders, and those that focus on other groups of professional investors. The taxonomy is summarized in Table 2.3.

TABLE 2.3 – Tests of the strong form EMH

Tests of strong form EMH

Type of Test	Evidence in favour EMH	Evidence against EMH
I.- Corporate insiders		
	Sharpe (1981)	Jaffe (1974), Aboody and Baruch (2000)
II.- Groups of professional investors		
Stock exchange specialists	Harris and Panchapagesan (2005)	
Security analysts	Shane and Stock (2006)	
Professional money managers (Mutual funds)	Treynor (1965), Sharpe (1966), Jensen (1969), Sauer (1997)	Grinblatt and Titman (1992)

Source: Own elaboration

The seminal paper on corporate insiders is Jaffe (1974a,b), who analyzes the trades executives and large shareholders performed on stocks of their own companies, to conclude they were able to obtain excess profits. Since then, most studies obtained empirical evidence against the strong form EMH. These include Demsetz and Lehn (1985), Seyhun (1988), Beneish and Vargus (2002) and Ke, Huddart and Petroni (2003). Nonetheless, some results in favor of the strong hypothesis are also available. These include Trivoli (1980), who notices the increasing effectiveness of regulation, and Sharpe (1981), who suggests investment funds make insider information less valuable because the number of potential imitators of a given strategy increases. Recent literature has focused on the sources of insider trading gains (Aboody and Baruch, 2000), their ability to perform as contrarian investors (Lakonishok and Lee, 2001), the effects of regulation and firm's ownership (Fidmuc, Goergen and Renneboog, 2006), the credibility of voluntary disclosure (Gu and Li, 2007), and legal insider trading contribution to efficiency (Aktas, Bodt and van Oppens, 2008), among other topics.

Among tests of insider information for groups of professional investors, the most common type are tests that analyze the performance of mutual fund managers. The classic papers are Treynor (1965), Sharpe (1966) and Jensen (1969), who obtained evidence in favor of the strong-form EMH. More significant was their contribution to the study of the investment management performance, providing measures such as the Sharpe and Treynor ratios and Jensen's alpha. Most literature supports the strong-form efficient hypothesis, including Kon and Jen (1978), Sauer (1997) and Bilson, Frino and Heaney (2005). The main evidence is the lack of a consistent outperformance by fund managers over a series of years. For the only relevant anomaly observed, the hot hands effect,[60] there is no consensus on whether this implies past fund returns are helpful to predict future performance (e.g., Grinblatt and Titman, 1992) or not (e.g., Pätäri, 2009). Similar tests have focused on other groups of professional investors, such as stock exchange specialists (e.g., Harris and Panchapagesan, 2005) and security analysts (Shane and Stock, 2006). We may conclude that most tests of the strong-form EMH provide strong evidence against EMH in what corporate insider trading is referred, and strong positive evidence in favor of the EMH in what professional investors' ability to consistently beat the market is referred.

2.5. CONCLUDING REMARKS

In this chapter we have given an extensive review of how efficiency is analyzed in the context of financial markets. In what follows we summarize the main topics discussed. First, we interpreted the efficient market hypothesis and, in particular, the key aspect of the informational efficiency of financial markets. Then, we described the three main elements that determine informational efficiency: namely, expectations, information and the discount factor.

Second, we discussed whether the EMH is testable or not, presenting several critiques that have been posed in regards of its testability. These include the confusion of the two alternative definitions of

[60] Hendricks, Patel and Zeckhauser (1993) observed that a hot-hands phenomenon was consistent during 1974–87: mutual funds that performed well one year continued to outperform in the following year.

the EMH, the joint hypothesis problem, some approaches behaviorists have provided to test the EMH, and an alternative interpretation of how markets operate according to the adaptive market hypothesis.

Third, we provided a taxonomy and a brief review of the empirical tests of the weak, semi-strong and strong form of the EMH available in the literature. The mixed evidence of market efficiency that stems from this review, together with the theoretical challenges exposed by the behavioral finance —the critics to its testability, the struggle to refute excess volatility and limits to arbitrage simultaneously— lead us to have further insight on behavioral finance. We do it in the subsequent chapter.

CHAPTER 3. EFFICIENCY IN FINANCIAL MARKETS: BEHAVIORAL FINANCE

3.1. INTRODUCTION

Behavioral finance is the most relevant field within behavioral economics. Behavioral economics has provided evidence of how non-standard preferences, non-standard beliefs, and non-standard decision making lead to an unconventional behavior by people in their economic decisions (DellaVigna, 2009). For instance, when people choose their retirement savings, use their credit cards, pay not to go to the gym, devote more or less effort at their jobs, give to charities, go on strike in response to wage cuts, neglect some costs and opaque or complex information, avoid to make decisions or tend to choose familiar or salient options, exploit consumer biases or voter inattention, and many others. However, if there is a field within behavioral economics that has been productive and successful to challenge the rationalist interpretation, that is behavioral finance applied to financial markets.

Behavioral economics represents a *return to reality* (Shiller, 2005) that criticizes the rational optimizing model as the only possible framework, and suggests instead a wider approach based on a combination of all social sciences. It combines psychology and economics to explain why and how people make seemingly irrational or illogical economic decisions (Belsky and Gilovich, 1999). Moreover, it may also feature relationships with sociology and anthropology (Shiller, 2000a), demography and history (Shiller, 2000b). It follows the conviction that an increasing realism of the psychological foundations will improve the fields of economics and finance (Camerer and Loewenstein, 2004). The more realistic our assumptions about the economic actors, the better our economics will be (Rabin, 2002a).

Behavioral finance would be *open-minded finance* (Thaler, 1993), dealing with the influence of psychology in financial decision making and financial markets (Shefrin, 2001a). It does not imply a global rejection of efficiency, utility maximization and equilibrium, but standard finance is so weighted down with anomalies that it makes sense to reconstruct it based on behavioral lines (Statman, 1995). Psychology provides alternative views to the standard finance's *homo economicus* about how people do behave (as opposite to how they should behave). According to this view, markets are not something that is outside us, it is *us*; how we perceive, how we want it to be, and how we study it are inextricably intertwined (Frankfurter, McGoun and Allen, 2004). Textbook economics teaches the benefits of free markets, presenting capitalism as essentially stable since people in free markets behave rationally and exhaust all mutually beneficial opportunities to produce and exchange (Akerlof and Shiller, 2009a).

Behavioral finance, instead, interprets markets may be guided by Keynes's animal spirits as well: sometimes we are irrational, wrong, shortsighted, or evil; others we hold to non-economic values like fairness, honor, or justice; and prices, many times, seem to be correlated with social changes. This view justify why markets might be inefficient.

However, changes in scientific paradigms never come without acrimony. Behavioral finance is an area with a growing acceptance and recognition among academics and authorities,[61] but rationalists still argue that anomalies are no more than methodological limitations. The goal of Chapter 3 is to provide an extensive review on the groundbreaking research on behavioral economics and finance. This serves two purposes. First, to show the foundations on which behaviorists have laid their theories about markets. The study of most of these theories, nonetheless, exceeds the scope of this thesis, so we will only provide a brief summary in this chapter (see Section 3.3). Second, it will help us familiarize with the myriad of biases and anomalies that pervade standard decision making and challenge the efficiency postulates of standard finance. These biases and anomalies will be extensively reviewed in Part II, particularly in Chapter 4, providing us a solid basis to decide on which aspects of the behavioral literature we want to focus on Part III —i.e., the experimental research and theoretical models.

The remainder of the chapter is organized as follows. Section 3.2 reviews the foundations of behavioral finance, mainly in chronological order. Section 3.3 introduces the most recent theories developed in search for a unified theory. Section 3.4 concludes with some remarks.

3.2. THE FOUNDATIONS OF BEHAVIORAL FINANCE

This section is devoted to review the main landmarks of behavioral finance. To facilitate understanding, the survey follows primarily a historical approach, describing first some of the early antecedents (subsection 3.2.1), followed by the main achievements by the researchers that pioneered this literature (subsection 3.2.2). Finally, how these and other groundbreaking researchers came to challenge the orthodoxy during the 1980s to 2000s is summarized in subsection 3.2.3.

3.2.1. The antecedents

Some authors go as far as Adam Smith's (1759) "The Theory of Moral Sentiments" to trace the first link between economics and psychology. Camerer and Loewenstein (2004) notice that when economics was born as a science, psychology did not exist as such, so economists were the psychologists of their times: *"the book [by A. Smith] is bursting with insights about human psychology, many of which presage current*

[61] Ben Bernanke, in his testimony before the Financial Crisis Inquiry Commission on the 'Causes of the recent financial and economic crisis', Washington D.C., September 2, 2010, said *"it is frankly quite difficult to determine the causes of booms and busts in asset prices; psychological phenomena are no doubt important, as argued by Robert Shiller, for example"*. He explicitly referred to Shiller (2000b) and Akerlof and Shiller (2009a).

developments in behavioral economics. For example, Adam Smith commented (1759/1892, p. 311) that 'we suffer more... when we fall from a better to a worse situation, than we ever enjoy when we rise from a worse to a better'. Loss aversion!" (p. 5). Then, the work "The Crowd: A Study of the Popular Mind", by Gustave Le Bon (1896), is considered to be an influential book in social psychology for its analysis of crowds from the psychological point of view and the study of their 'mental unity'.[62]

Selden (1912) was probably the first to suggest prices may be dependent on the mental attitude of investors, identifying psychology as a main driver of financial markets. Some concepts he would introduce, such as panics, booms, fear of a loss, speculative cycles or deviations from rationality ('inverted reasoning'), were to be used by the behavioral finance later on. An early critique to the axioms of the expected utility hypothesis was introduced by French economist Maurice Allais (1953): the so-called Allais paradox would later be exploited by Daniel Kahneman and Amos Tversky in their prospect theory. A cornerstone in the behavioral literature is also the notion of *bounded rationality*, introduced by Herbert Simon (1955, 1957). Simon suggests decision makers should be viewed as boundedly rational, with utility maximization being replaced by satisficing (Kahneman, 2003a). Simon also represents an antecedent for the concept of *heuristics*: since information is vast but people have limited information-processing abilities, they construct simplified models of the world to decide.

Festinger, Riecken and Schachter (1956) and Festinger (1957) introduce the concept of *cognitive dissonance*: when two cognitions[63] are inconsistent, an unpleasant state of cognitive dissonance follows. The book "When Prophecy Fails" reports their experiences when they infiltrate in a group of believers that the end of the world was about to come, and a flying saucer from outer space would rescue in a due date only those who truly believed. Their goal was to analyze what would believers do as cognitive dissonance arises when the prophecy of the UFO coming fails, and found believers may become even more convinced if some conditions hold.[64] Then, Festinger (1957) elaborates a theory of cognitive dissonance. Two elements are dissonant if they do not fit together. The existence of dissonance, being psychologically uncomfortable, motivates the person to try to reduce it. Either some attempts are made to rationalize them, or to avoid situations and information which would likely increase the dissonance.[65]

---

[62] Psychology asserts that, beyond instincts, passions and feelings, individuals are guided by rational intelligence. However, Le Bon (1896) describes some circumstances —e.g., a contagion effect and individual responsibility disappearing in the anonymity of crowds— that may form a collective mind with different characteristics from those of the individuals that compose it.

[63] Following Festinger (1957), cognitions are things a person knows about herself, her behavior and her surroundings.

[64] Believers must had strongly committed to their faith or to the group, doing some actions that are difficult to undo. The belief must have some relation with what believers do, such that when they commit they also give support to their beliefs. Besides, they need a group: a single believer probably would not be able to persevere, but social support helps them believe.

[65] About ways to rationalize the dissonance, there is the classic example of a smoker, who knows it is bad for his health but thinks (a) he enjoys smoking so much; (b) health damages may not be so serious; (c) he can't avoid every possible dangerous contingency and still live; (d) perhaps if he stopped smoking he would put on weight. Festinger (1957) relates several ways to reduce dissonance. First, by changing a behavioral cognitive element. We often change our behavior and feelings in accordance to new information. Second, by changing an environmental cognitive element. This is sometimes impossible, except in extreme cases which might be called psychotic. Third, and perhaps more common, it is possible to reduce the magnitude of dissonance by adding new cognitive elements. For example, a smoker may actively seek new information —e.g., opinions critical of the perils of smoking— that would reduce the dissonance he feels, while at the same time he avoids reading that research.

Following their research on cognitive dissonance, Festinger and Carlsmith (1959) analyze the effects of forced compliance and the dissonance it generates. This represents a prelude to Stanley Milgram's experiments on *obedience to authority*. When a person is forced to do or say something contrary to her opinion, her personal opinions may change under some conditions as to bring them closer to the behavior she was forced to perform. Later, Stanley Milgram (1963, 1974) would conduct his famous experiment to show most people were able to perform acts that violate even their deepest moral beliefs, with relatively few people having the initiative needed to resist authority.[66]

Finally, other antecedents are Oskamp (1965) and Alpert and Raifa (1969) on *overconfidence*, Chapman and Chapman (1971) and Langer (1975) on *illusion of control*, and Edwards (1968) about *conservatism*.[67] Oskamp (1965) analyzed, in the context of clinical practice by psychologists, whether their confidence to make diagnostic conclusions is justified by a corresponding increase in accuracy. He finds confidence increases with information, but no evidence of a significant increase in accuracy. Alpert and Raifa (1969) analyze overconfidence when individuals assess probability distributions of uncertain quantities. Edwards (1968) observes conservatism in how individuals process new information: opinion changes are orderly and usually proportional to the outputs of the Bayes' theorem, but insufficient in amount. Chapman and Chapman (1971) identify an illusory correlation, that is, a tendency to see two events occur together more often than they actually do. Finally, Langer (1975) identifies an illusion of control: people behave as though chance events are subject to control.

3.2.2. Groundbreaking research

In this section we review the main achievements by the researchers that pioneered the literature on behavioral finance and economics. These are Daniel Kahneman and Amos Tversky, Richard Thaler, Robert Shiller, Hersh Shefrin and Meir Statman.

If there is a milestone in behavioral economics, that must be acknowledged to Daniel Kahneman and Amos Tversky's articles in the 1970s. Their most acclaimed paper, *Prospect theory: An analysis of decision under risk*, was published in 1979. Nonetheless, some years before, they already started to contribute to the field introducing three relevant heuristics: representativeness, the availability heuristic, and anchoring-and-adjustment. Heuristics, from the Greek word *eureka* ('to find' something), refer to the way people perceive, process and evaluate the probabilities of uncertain events in the context of decision making under risk. They are rules of thumb people use to make financial decisions:

[66] In particular, participants in the experiment were required to give fake (but they were unaware of it) electro-shocks up to 450 volt to other participants, to the extent to cause them severe damages or even death. *"I set up a simple experiment at Yale University to test how much pain an ordinary citizen would inflict on another person simply because he was ordered to by an experimental scientist"* (Milgram, 1974). They were not compelled to do it under coercive methods, only asked to do it because it was required for scientific purposes.

[67] Other authors that deserve to be mentioned are Slovic (1972), who noted the importance of analyzing human information-processing limitations and its effects over judgmental accuracy in investment analysis, and Meehl (1954), who wrote about the controversy on clinical versus statistical prediction —that is, the evidence that algorithmic methods make better predictions of human behavior than (subjective) clinical procedures.

information in financial markets is vast and changes every second, hence heuristics help to provide simple means to make a decision. However, empirical evidence shows people use subjective probability estimates that deviate from objective probability in a systematic way (Kahneman and Tversky, 1972).

People exhibits *representativeness* when they assess the subjective probability of an event by the degree to which it is similar in essential characteristics to its parent population, and it reflects the most relevant features of the process by which it is generated. Kahneman and Tversky (1972) find empirical evidence of probability judgments being determined by the most salient characteristics of the sample,[68] even in the intuitive judgments of expert psychologists. Representativeness also shows people view chance as unpredictable but essentially fair: we expect short sequences of, for example, coin tosses, to include about the same number of heads and tails, as if a 'law of small numbers'[69] applied as well (Tversky and Kahneman, 1971). The *availability heuristic*, introduced by Tversky and Kahneman (1973), describes the tendency to evaluate the probability of events or the relevance of information depending on the degree to which information is readily available, memorable or vivid, even when there are better sources of information: for instance, we may assess the divorce rate in the country by recalling divorces among our acquaintances. Availability is a useful clue for the judgment of frequency because frequent events are easier to recall, but since it also depends on other factors different from true objective frequency, this heuristic leads to systematic biases. Finally, Tversky and Kahneman (1974) describe *anchoring-and-adjustment*. Anchoring refers to people being influenced in their assessments by arbitrary data, even when they are non-informative (Hens and Bachmann, 2008).[70] Besides, in some situations people adjust the initial value they obtain as to yield the final answer they expected, a behavior known as adjustment.

In 1979, Kahneman and Tversky published one of the most cited papers in economics. Kahneman and Tversky, 1979 introduce *prospect theory*, an alternative model to the expected utility theory (EUT) that would better describe how people make financial decisions in a context of uncertainty. In particular, they observe three effects that contradict EUT. First, people overweight outcomes that are considered certain (known as the certainty effect). Second, the reflection of prospects around zero —that is, with losses of a same magnitude replacing gains— reverses the preference order (denoted reflection effect).

---

[68] For example, respondents to a test answered that a sequence girl-boy-girl-boy-boy-girl for the exact order of births in families of six children is more likely than a sequence boy-girl-boy-boy-boy-boy, when they are, indeed, equally likely. They did so because the sequence with five boys and one girl fails to reflect the proportion of boys and girls (50-50) in the population. The same representativeness bias appears when comparing sequences BBBGGG and GBBGBG. Both reflect the proportion of boys and girls in the population, but the first one appears to be less random.

[69] The law of large numbers, first enunciated in Bernoulli's (1713) *Ars Conjectandi*, ensures very large samples are highly representative of the populations from which they are drawn. However, the results observed by Tversky and Kahneman (1971) would imply a belief in what they called the 'law of small numbers', that is, as if the law of large numbers applies to small numbers as well.

[70] Different starting points yield different estimates, which are biased toward the initial value. Tversky and Kahneman (1974) feature a classic experiment where several subjects were asked to estimate some percentages after a wheel-of-fortune with numbers from 0 to 100 was spun in their presence. The results evidence they anchored their estimations to the random numbers obtained by the spinning wheel, which are non-informative.

Third, people generally discards elements that are shared by all prospects, and focus only on the components that distinguish them (known as the isolation effect).

The identification of these effects led Kahneman and Tversky to propose an alternative theory of choice, prospect theory, where the utility function is replaced by a value function that is assigned to gains and losses —as deviations from a *reference point* that is taken to be the status quo— rather than to final assets, and where probabilities are replaced by decision weights.[71] Under this theory, people would exhibit risk aversion for gains (meaning a concave value function for positive values) and risk-seeking for losses (a convex value function for negative values), with the value function being steeper for losses than for gains (implying loss aversion). Further insight was provided by Tversky and Kahneman (1981), where they introduce the concept of framing in decision making,[72] Kahneman and Tversky (1984), where the concept of *loss aversion* was first coined, and Tversky and Kahneman (1986), where they suggest deviations of actual behavior from the normative model are too widespread to be ignored. An extended version was developed in Tversky and Kahneman (1992), called *cumulative prospect theory*, CPT. It extends the original model as it employs cumulative rather than separable decision weights,[73] applies to uncertain as well as to risky projects with any number of outcomes, and allows for different weighting functions for gains and losses. Experimental evidence would later confirm the distinctive fourfold pattern of risk attitudes predicted by this theory: risk aversion for gains and risk seeking for losses of high probability; risk seeking for gains and risk aversion for losses of low probability.

In his Nobel Prize lecture and subsequent articles, Kahneman (2003a,b) acknowledges their findings became useful to economics when Thaler (1980) used them to explain riskless choices. Thaler shows loss aversion explains a violation of consumer theory known as *endowment effect*: the value of a good increases when the good becomes part of the individual's endowment.[74] Other situations where consumers fail to behave in accordance with the normative prescriptions of economic theory include failure to ignore sunk costs, underweighting opportunity costs, choosing not to choose and regret, and precommitment and self-control. Thaler (1980) also formally introduces the concept of *mental accounting*: the cognitive process by which people evaluate their financial activities. Then, in three subsequent articles, he extends the analysis of consumer anomalies.

[71] Decision weights, introduced by Fellner (1961) to explain aversion to ambiguity, are not probabilities: they do not obey the probability axioms and are generally lower than the corresponding probabilities, except in the range of low probabilities. These overweighting of low probabilities explain the attractiveness of insurance and gambling (Kahneman and Tversky, 1979).

[72] Tversky and Kahneman (1981) use the term *decision frame* to refer to the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice. They show that, because of imperfections of human perception and decision, changes of frame often reverse preferences between options.

[73] The weighting scheme in Kahneman and Tversky (1979) is a monotonic transformation of outcome probabilities that exhibits two problems: it does not always satisfy stochastic dominance, and it is not readily extended to prospects with a large number of outcomes. CPT solves both problems: it assumes transparently dominated prospects are eliminated in the editing phase, and normalizes the weights so that they add to unity.

[74] The selling price appears to be much higher than the buying price, often by a factor of 2 or more, which is inconsistent with economic theory. Loss aversion would be a plausible explanation since the value of a good appears to be higher when the good is viewed as something that could be lost than when it is seen as a potential gain (Kahneman, Knetsch and Thaler, 1990).

First, Thaler (1981) analyzes the dynamic inconsistency of consumer choice, showing people discount gains more than losses (a behavior known as sign effect) and large outcomes less than small ones (known as the magnitude effect). Second, Thaler and Shefrin (1981) introduce the concept of self-control in intertemporal choice. They provide a rationale for individuals to impose themselves constraints on their future behavior, assuming any person is two-fold: a farsighted planner with long-run preferences who is concerned with lifetime utility, and a myopic doer that exists only for one period, has short-run preferences and is completely selfish.[75] Thaler and Shefrin then model self-control as an internal conflict resembling the principal–agent conflict. Some techniques to alter incentives and rules that restrict opportunities, such as precommitment or self-imposed rules of thumb, could be used to solve the conflict. Third, Thaler (1985) develops a model of consumer behavior. He suggests framing may be a variable that explains the consumer's optimal behavior, but framing itself cannot alter behavior. Thus, he analyzes consume under a prospect theory approach: the value function replaces the utility function, and prices are introduced in the value function using the concept of a reference price. Then, if a mental coding of combinations of gains and losses using the prospect theory —i.e., mental accounting— is assumed, Thaler shows individuals violate some basic economic principles.

Thaler's main contribution to behavioral finance came in 1985 as well. The article by De Bondt and Thaler (1985) *Does the stock market overreact?* sets the first link between behavioral biases and the efficient market hypothesis. They analyze whether the tendency to overreact to unexpected and dramatic news events may affect stock prices, and find evidence of overreaction surviving the process of arbitrage. If stock prices systematically overshoot, then their reversal should be predictable from past returns, which violates the weak-form EMH. Focusing on stocks that experienced extreme capital gains ('winners') or extreme losses ('losers') over periods up to five years, they find evidence that loser stocks tend to be future winners, confirming overreaction in capital markets.

The testing of the EMH by a behavioral researcher was pioneered, nonetheless, by Robert Shiller. As we saw in Chapter 2, Shiller (1979, 1981) imposed a theoretical limit on bond market and stock market volatility. In particular, Shiller (1979) shows that the EMH implies that long term interest rates should not be too volatile, contrarily as it is empirically observed. Likewise, Shiller (1981) shows stock prices are too volatile to be justified by new information about future dividends. The demonstration of these anomalies, as we will see in Chapter 4, does not require a behavioral interpretation, but Shiller would later provide it. Shiller (1984) claims that investing in speculative assets is a social activity. This means that mass psychology is the key factor that explains price movements in stock markets: investors discuss their investments with other people, read about investments, gossip about other investors' failures or successes, etc. As a consequence, security prices fluctuate following fads, just like they do in

[75] Authors claim to be the first to provide a formal treatment of a two-self economic man, though they granted the idea to economists like Adam Smith (1759) or psychologists such as Freud (1958).

other popular instances —e.g., food, clothes or politics. This way, Shiller gave a social interpretation to behavioral biases such as herding, momentum, optimism, under and overreaction, and more.

Finally, a review of the groundbreaking research in behavioral finance is only complete if it mentions the early work of Hersh Shefrin and Meir Statman. Shefrin had already made his first contribution to behavioral economics in Thaler and Shefrin (1981) mentioned above. However, it is his work with Statman (Shefrin and Statman, 1984, 1985) that represents, according to many, the dawn of the behavioral finance. In these two papers they provide two models which, based on behavioral concepts recently developed, were able to explain two observed phenomena that concerned people in the academics and the industry for long. On one hand, Shefrin and Statman (1984) explains the *dividend puzzle*[76] based on four major elements: prospect theory (Kahneman and Tversky, 1979), mental accounting (Thaler, 1980), the theory of self-control (Thaler and Shefrin, 1981), and regret aversion. Firms would pay dividends because investors exercise better self-control if they are given dividends than if they have to sell shares —which might lead to a liquidation of the portfolio faster than desirable. Shefrin and Statman (1985), on the other hand, provide a first insight on anomalies of trading activities, the most relevant being the *disposition effect*: investors exhibit a general disposition to sell winners too early and ride losers too long.[77] Shefrin and Statman suggest the disposition effect is part of the general folklore about investing, though it has no interpretation under standard finance models. This theory was later confirmed in a series of papers by Odean (1998a, 1999) and Barber and Odean (2001, 2002).

3.2.3. 1980 – 2000: A challenge to orthodoxy

Since the 1980s, the pieces of evidence against standard finance by behaviorist researchers increased exponentially, to the point of setting behavioral finance in a position to become the new orthodoxy in finance. Three relevant topics in the literature during these years were herding, underreaction and the limits of arbitrage. The early research on these topics is reviewed in what follows, while other relevant contributions are outlined afterwards.

The tendency of agents to follow the herd, that is, to mimic the investment decisions of other investors, is known as herding. Selden (1912) and Keynes (1936) were probably the first to suggest investors make decisions influenced by what other investors do, but the first to model a herd behavior were Scharfstein and Stein (1990) and Banerjee (1992). The first paper provides a model, valid both for corporate investment decisions and the stock market, based on a principal–agent problem where the

[76] The dividend puzzle refers to the evidence of the persistence of firms paying dividends to their shareholders in spite of the recognition that share repurchases are a means of cash distribution that confer tax advantages (Subrahmanyam, 2007).

[77] Shefrin and Statman see in this behavior the aversion to a sure loss predicted in prospect theory. Indeed, the theoretical framework used in Shefrin and Statman (1985) is an extension based on the four elements used in the 1984 paper: prospect theory predicts winners will be sold and losers will be hold when the proceeds are held, rather than rolled over into another gamble; mental accounting clarifies when the disposition effect holds if realization proceeds are reinvested in another gamble; regret aversion would be an important rationale for investors having difficulty in realizing both gains and losses; and self-control explain the rationale for methods investors use to force themselves to realize losses.

distortion in incentives plays a key role: herding is rational from the perspective of managers who are concerned about their reputations in the labor market. Banerjee (1992), instead, develops a model of with no incentive distortion that sets the basis for future analyses of herding. Under a sequential decision model where each decision maker rationally looks at the decisions made by previous agents, the equilibrium decision rule is shown to be characterized by extensive herding: *"agents abandon their own signals and follow others, even when they are not really sure that the other person is right" (p. 807)*. Banerjee suggests herding might be a good explanation for the excess volatility: in his model, since the herd externality is of a positive-feedback type, the signals generated by the first few decision makers determine 'where the first crowd forms', while the others join the crowd and amplify the effect.

Two years before that, Jegadeesh and Titman (1993) pioneered the study of *momentum*.[78] De Bondt and Thaler (1985) had previously found evidence of overreaction for periods up to five years, but professional managers and investors still used relative strength as a selection criterion. Jegadeesh and Titman assume that, for both strategies to be profitable, either the abnormal returns of momentum strategies are spurious, or the discrepancy is due to the different time horizons used in the trading rules. Thus, they analyze 32 different strategies and find that the return of all the zero-cost portfolios (buying winners, selling losers) generate positive returns over 3 to 12 month holding periods —though half of the abnormal returns dissipates in the following two years. They also confirm that the momentum strategy works because of delayed price reactions to firm-specific information (implying market inefficiency) and not because of the higher systematic risk or lead-lag effects from delayed stock price reactions to common market factors.

A key step for behavioral finance to provide an alternative interpretation to the efficient markets is the literature on the limits of arbitrage. A classic objection to behavioral finance interpreted as a 'collection of anomalies' is that, even if some agents were less than fully rational, rational agents would avoid systematic deviations of security prices from fundamental values through arbitrage (Barberis and Thaler, 2003). Hence, a rationale for arbitrage to be limited was necessary for behavioral finance to succeed as an emerging theory. The limits of arbitrage show how a market with both rational and irrational traders can drive prices towards market inefficiency. Arbitrage, as it is traditionally defined,[79] requires no capital, entails no risk, and brings prices to fundamental values. Shleifer and Vishny (1997) came to suggest instead real-world arbitrage is risky and limited. Arbitrageurs are highly specialized professional agents who manage other investors' capital and who may incur in temporary losses. Here an agency problem arises. Shleifer and Vishny provide then an agency model of limited arbitrage,

[78] An early article is Levy (1967), who finds a positive relationship between buying stocks with high historical prices and future outperformance. However, Jensen and Bennington (1970) attribute the result to data mining.

[79] Arbitrage is the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices (Sharpe and Alexander, 1990). Friedman (1953a) was the first to assert arbitrage would ensure market efficiency, even if not all investors are rational: irrational investors would lose money, but they cannot lose money forever, so they would eventually disappear (Shleifer, 2000).

showing arbitrage is ineffective in extreme circumstances: basically, when assets are significantly mispriced and arbitrageurs are fully invested.

Shleifer and Vishny (1997) worked their theory about the limits of arbitrage on the concept of *noise trader risk* —the risk of noise traders' beliefs not reverting to the mean for a long time— by DeLong et al. (1990a), who in turn borrow from Black's (1986) concept of noise:[80] people trade on noise as if it were information and causes markets to be inefficient, but it prevents investors from taking advantage of inefficiencies, too. DeLong et al.'s (1990a) model helps to explain some financial anomalies, like the mean reversion of stock returns, the closed-end fund puzzle, the excess volatility and the equity premium puzzle.[81] In a scenario where perfect substitutes are available, arbitrageurs focus on exploiting noise traders' misperceptions. However, arbitrageurs are likely to be risk averse and have short horizons, so their ability to take positions against noise traders is limited: thus, there is a chance that noise traders' beliefs will not revert to their mean for a long time, or even become more extreme in the meantime. As a result, if an arbitrageur has to liquidate his positions before the price eventually recovers, he suffers a loss. Being aware of this in advance, the fear of a loss forces the agent to limit his original arbitrage position.

Finally, a classic in the literature of limits of arbitrage is the rationale for an aggregate-market inefficiency. Authors like Figlewski (1979), Campbell and Kyle (1993) and Siegel (1998) suggest the impossibility to pin down stock or bond markets because a close substitute cannot be found. The idea that markets may be efficient from a micro but not from a macro perspective (for the aggregate market) gained relevance after the 'Samuelson's dictum' (Jung and Shiller, 2006):[82] *"Modern markets show considerable micro efficiency (... the minority who spot aberrations from micro efficiency can make money from those occurrences and... wipe out any persistent inefficiencies). In no contradiction to the previous sentence, I had hypothesized considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values"* (p. 221). Jung and Shiller (2006) agree macro inefficiency is plausible because there is more information available about future changes in fundamentals of individual firms than of the aggregate stock market.

Beyond limits of arbitrage, differences in opinion (Harrison and Kreps, 1978) are shown to provide a rationale for speculative markets. Several authors extended the analysis on the relationship between noise, heterogeneous expectations and speculative markets. An example is Cutler, Poterba and Summers (1990, 1991), who follow Kindleberger (1978) to model asset price dynamics when investors follow heterogeneous trading strategies. They show empirical evidence of speculative dynamics on

[80] Black (1986) identifies three sources of noise: a large number of small events; noise as uncertainty about prices in the future; and noise in the form of expectations that need not to follow rational rules.

[81] Three relevant papers about the closed-end fund puzzle, the excess volatility and the equity premium puzzle are Lee, Shleifer and Thaler (1991), Campbell and Kyle (1993) and Benartzi and Thaler (1995), respectively. They are reviewed in Chapter 4.

[82] Shiller (2000) and Jung and Shiller (2006) quote this excerpt from a private letter by Paul Samuelson to John Campbell and Robert Shiller, reflecting a point Samuelson had set explicitly already in Samuelson (1998).

returns on stocks, bonds, foreign exchange, real estate and other assets. These years witnessed as well the controversy on overreaction, underreaction and momentum. On one hand, De Bondt and Thaler (1987), Fama and French (1988a,b), Poterba and Summers (1988) and Campbell and Shiller (1988a,b), among others, reported additional evidence supporting the overreaction hypothesis. Jegadeesh (1990), Lehmann (1990) and Lo and MacKinlay (1990) also find evidence of a reversal behavior of extreme winners and losers. On the other hand, early papers showing evidence of underreaction and momentum include Bernard (1992), Michaely, Thaler and Womack (1995), Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Ikenberry, Lakonishok and Vermaelen (1995), Ikenberry, Rankine and Stice (1996), and Rouwenhorst (1998).

Some authors suggested a rationalist interpretation for overreaction, including Chan (1988) and Ball and Kothari (1989), who argue that contrary investing profits are due to a failure to correctly account for risk-adjusted returns, and Zarowin (1989, 1990), who argues they are related to the size effect (Banz, 1981).[83] However, the evidence of momentum profitability stood out as a major unsolved puzzle: much research at that time was conducted to explain reversals in stock prices, but satisfactory explanations were still not available.[84] Thus, Chan et al. (1996) try to rationalize the existence of momentum. They analyze different strategies that exploit market underreaction to two pieces of publicly available information —namely, past returns and recent earnings surprises— and confirm that drifts in future returns over the next six and twelve months are predictable from them.[85] Then, they pose a question: is there a contradiction between evidence of underreaction and contrarian overreaction?

A full reconciliation of both theories would be an open area of research during the subsequent years. Chan et al. (1996) provide a first intuition: perhaps they are not incompatible, since a common element is a market's tendency to anchor too heavily on past trends. Barberis, Shleifer and Vishny (1998) noticed as well that most researchers agree overreaction happens over long horizons (e.g., De Bondt and Thaler, 1985) while momentum tends to be profitable over short horizons (e.g., Jegadeesh and Titman, 1993). Consequently, they propose a model of investor sentiment motivated on the representativeness heuristic and conservatism. Extrapolation from random sequences, wherein agents expect patterns in small samples to continue, creates overreaction, while conservatism creates

[83] Chopra, Lakonishok and Ritter (1992) and Lakonishok, Shleifer and Vishny (1994) later evidenced that contrarian investing yields higher returns because they exploit a suboptimal behavior of investors and not because they are fundamentally riskier.
[84] Chan, Jegadeesh and Lakonishok (1996) cite these possible explanations for overreaction: bid-ask spreads (Kaul and Nimalendran, 1990; Jegadeesh and Titman, 1995), lead-lag effects between stocks (Lo and MacKinlay, 1990), investors' tendency to overreact (De Bondt and Thaler, 1985, 1987; Chopra et al., 1992), microstructure biases (Ball, Kothari and Shanken, 1995; Conrad and Kaul, 1993), time-variation in expected returns (Ball and Kothari, 1989), and differences in book-to-market value of equity (Chan, Hamao and Lakonishok, 1991; Fama and French, 1992; Lakonishok et al., 1994). However, not even Fama and French's three-factor model was able to account for it. Possible explanations for the profitability of momentum strategies that were probed before Chan et al. (1996) were that medium-horizon returns could be related to earnings surprises (Affleck-Graves and Mendenhall, 1992) or that positive feedback trading strategies (DeLong et al., 1990) could induce such profitability.
[85] Chan et al. (1996) suggest conservatism might be an alternative explanation for the profitability of momentum strategies. In this sense, Basu (1997) interpret conservatism as the accountants' tendency to require a higher degree of verification for recognizing good news than bad news in financial statements, resulting in earnings reflecting bad news more quickly than good news, and causing systematic differences and earnings persistence.

momentum through underreaction. The model helps explain statistical evidence of underreaction of stock prices to a news announcement, and overreaction to a series of good or bad news announcements. Daniel, Hirshleifer and Subrahmanyam (1998) propose another model to explain under and overreaction, but based on investor overconfidence and biased self-attribution.[86] In addition, Lee and Swaminathan (2000) suggest a theory to reconcile intermediate-horizon underreaction and long-horizon overreaction: they use past trading volume as a link between momentum and value strategies. Other early works that model investors' behavior in a way that they generate both under and overreaction include Frankel and Froot (1988), Hong and Stein (1999), and Veronesi (1999).

Beyond the debate on over and underreaction, the behavioral finance has also focused on providing additional insights on decision-making. Yaari (1987), for instance, modifies the expected utility theory in his so-called 'dual theory' of choice under risk: instead of requiring independence with respect to probability mixtures of risky prospects, it requires independence with respect to direct mixing of payments of risky prospects. Samuelson and Zeckhauser (1988) obtain experimental evidence that individuals disproportionately choose the status quo alternative —that is, doing nothing or maintaining one's previous decision. This is known as the *status quo bias*, a concept closely related to the endowment effect by Thaler (1980). Kahneman et al. (1990) analyze the discrepancies between willingness to accept (WTA) and willingness to pay (WTP),[87] which are not explained under the Coase theorem (Coase, 1960). Those discrepancies reflect an effect of reference positions on preferences, as suggested by the endowment effect. Kahneman *et al.* show the effect is a manifestation of loss aversion. Further insight of endowment effect, loss aversion and status quo bias is provided by Kahneman, Knetsch and Thaler (1991). Finally, Tversky and Kahneman (1991) present a reference-dependent theory of consumer choice based on prospect theory which explains status quo by a deformation of indifference curves about the reference point.

In the 1990s, Gigerenzer (1991, 1996) and Kahneman and Tversky (1996) engaged in a discussion on whether heuristics and biases are susceptible to represent large and systematic biases. Gigerenzer asserts that most errors in probabilistic reasoning —such as overconfidence, conjunction fallacy or base-rate neglect— are in fact not violations of probability theory, because researchers ignore conceptual distinctions fundamental to probability theory, such as the single case versus relative frequency.[88]

---

[86] Daniel et al. (1998) also provide a first response to Fama (1998), when he claims that the increasing evidence of overreaction and underreaction is not sufficient to dismiss the theory of market efficiency, because anomalies seem to distribute randomly between underreaction and overreaction. Daniel et al. (1998) respond arguing that the return patterns are strong and regular, occur in different international markets and in different time periods, and some of those patterns (they specifically refer to the post-corporate event and the post-earnings announcement drift) are obtained in the majority of event studies.

[87] WTA is the minimum compensation demanded by an individual to give up a good or to accept something undesirable; WTP would be, instead, the maximum amount she would be willing to pay in the opposite situation.

[88] For example, overconfidence would not be a violation of probability theory, since such theory is not violated if one's degree of belief (confidence) in a *single* event is different from the *relative frequency* of correct answers in the long run. For *frequentists,* the term probability referred to a single event has no meaning at all, probability theory is about frequencies. For *subjectivists* instead, probability is about single events, but rationality is identified with the internal consistency of subjective probabilities: there is no empirical criterion to prove an individual evaluation of the probability of an event to be right or wrong.

Kahneman and Tversky respond that Gigerenzer misrepresents their work for two reasons. First, biases and heuristics are not exclusively concerned with biases in assessments of subjective probability —e.g., Kahneman and Tversky (1974) discuss twelve biases and only two involve subjective probability—but Gigerenzer *"dismisses the entire body of research because of a debatable philosophical objection to two of twelve phenomena"* (p. 583). In fact, Gigerenzer's argument would lead to the conclusion that there is no normative basis for diagnosing whether any judgment is wrong or biased. Second, he misrepresents their position when characterizing judgmental heuristics as independent of context and content, when in fact framing has been a hallmark of their theory. Furthermore, they assert Gigerenzer ignores critical evidence that judgments of frequency are susceptible to large and systematic biases.[89]

Eventually, by the new millennium behavioral finance was no longer as controversial as it once was (Thaler, 1999a) and was on the verge of going mainstream (Rabin, 2002a). Thus, the leading behaviorists condensed the knowledge developed so far in several books and literature review articles. Rabin (1998) enumerates the basic psychological phenomena that contradict the expected utility theory, including mild biases, severe biases in judgment under uncertainty, and psychological findings that represent a radical critique of the utility model. Shiller (2000a) makes a list of theories from other social sciences used by researchers in finance, that have done most of the work on understanding less-than-perfectly rational human behavior. Relevant ones are prospect theory, mental accounting, regret and cognitive dissonance, anchoring, overconfidence, over and underreaction, and representativeness.

Three classic books at the time were Kahneman and Tversky (2000) "Choices, values and frames", Shefrin's "Beyond Greed and Fear" and Shiller's "Irrational Exuberance".[90] The former is a selection from their collaborative research on prospect theory. Shefrin (2000) provides a review of the three basic themes that underlie behavioral finance: how heuristic-driven biases and frame dependence lead to inefficient markets. Shiller (2000b) provides evidence that the stock market was significantly overvalued for reasons ranging from structural factors (internet, the decline of foreign rivals, materialistic values, baby boom, capital gains tax cuts, rise in pension plans and mutual funds), amplification mechanisms, cultural factors (news media, 'new era economic thinking'), psychological factors (anchors, herd behavior), and others. Shleifer (2000) and Barberis and Thaler (2003) condense behavioral finance in two building blocks: limits of arbitrage and psychology ('market sentiment' in Shleifer's terminology). Finally, Gilovich, Griffin and Kahneman (2002) edit "Heuristics and Biases: The Psychology of Intuitive Judgment", a book that compiles the most influential research in heuristics and biases since their 1982 collection (Kahneman, Slovic and Tversky, 1982).[91]

[89] The debate would continue, since Gigerenzer (alone and together with other authors) has developed a line of thought somewhat critical with behavioral finance. The discussion is analyzed in 'heuristics', subsection 4.2.1 of Chapter 4.

[90] Shiller chose the term *Irrational exuberance* quoting Alan Greenspan's words in December 1996, when the former Chairman of the Federal Reserve expressed his concern with the excessive optimism in stock markets.

[91] Other publications include "Simple Heuristics That Make Us Smart" (Gigerenzer, Todd and the ABC Research Group, 1999), a book about 'fast and frugal heuristics' that looks for a plausible notion of rationality; Starmer (2000), who reviews several

3.3. THE FUTURE OF THE BEHAVIORAL ECONOMICS AND FINANCE

The main critique of the rationalist school (e.g., Fama, 1998) is that behaviorists should provide a unified theory alternative to the EMH about the functioning of financial markets. As Subrahmanyam (2007) reckons, this critique may well be true at this point. However, since traditional finance does not appear to be supported by data, it makes more sense to improve those theories that are consistent with evidence (behavioral finance). In addition, the behaviorists defend this critique would only be partly justified, for two reasons. Firstly, psychological theories of intuitive thinking cannot match the precision of formal normative models, but this only means rational models are psychologically unrealistic (Kahneman, 2003a). Secondly, there is no single unifying model in behavioral finance, but neither can it be found in other fields of economics which are organized around several small models describing specific mechanisms (Shleifer, 2000).

This subsection is devoted to review some of the most relevant of these models and theories that behavioral economics and finance have recently provided. In recent years, the research in the field has evolved to what Rabin (2002a) has called a 'second wave behavioral economics', which goes beyond a mere identification of problems with standard economic assumptions, to systematically exploring alternatives. However, we will only provide a brief summary of them, as the study of these theories exceeds the scope of this thesis. Namely, in what follows we review the following areas: decision theory; behavioral finance in financial markets; behavioral corporate finance; behavioral economics in consumption and inter-temporal decision making; debiasing techniques; and neuroeconomics.

Decision theory. Prospect theory is the best established model in behavioral economics (Rieger and Wang, 2008a), replacing EUT as the dominant descriptive theory of risky decision making (Birnbaum, 2008a). Indeed, Rabin's (2000) calibration theorem shows that no concave utility function can simultaneously explain plausible small-scale and large-scale risk attitudes, making expected utility theory an utterly implausible explanation for appreciable risk aversion over modest stakes. Following this, Rabin and Thaler (2001) pronounce the expected utility hypothesis dead.[92]

Nonetheless, being the best description available of decision making under risk and uncertainty, prospect theory is imperfect (Starmer, 2000; Birnbaum, 2008a). Birnbaum (2008a) notes there is

alternatives to expected utility theory, including decision weights, reference dependent models, and non-transitive preferences; Belsky and Gilovich (1999), who highlight the most relevant biases why people use to make big money mistakes; and Gigerenzer (2001) and Gigerenzer and Selten (2001), who develop the concept of ecologically bounded rationality: to think of rational behavior as people using an 'adaptive toolbox' of fast and frugal heuristics rather than optimizing calculus.

[92] Kahneman (1994) highlights two different notions of utility: *experienced utility* and *decision utility*. People correctly perceive the consequences of their decisions, but misperceive the utility derived from them. Thus, the experienced utility of an outcome measures the hedonic experience of such outcome, whereas the decision utility would be the weight assigned to that outcome in a decision. Both measures may be systematically different, and make the 'revealed preference' method flaw.

evidence of paradoxes violating both versions of prospect theory, too. Critics include Brandstätter, Gigerenzer and Hertwig (2006), Gonzalez and Wu (2003), Starmer (2000) and others, though often followed by controversy (e.g., Rieger and Wang, 2008a). Models trying to solve recent critiques to prospect theory include Birnbaum's (2008b) transfer of attention exchange model, Schmidt, Starmer and Sugden's (2008) third generation prospect theory, and Harrison and Rutström's (2009) proposal to reconcile EUT and PT using a mixture model. Finally, although originally a static model, prospect theory has been widely applied to dynamic settings in economics to understand work effort, brand choices, capital budgeting, stock returns, trading volumes, and option exercises (Arkes et al., 2010). Examples of dynamic settings of prospect theory include Heath, Larrick, and Wu (1999), Barberis and Huang (2001), and Grinblatt and Han (2005).

BF in financial markets. The greatest advances in the behavioral literature have come from the behavioral finance applied to financial markets. Traditional finance appears to be limited to understand three main issues: why do individual investors trade and how they perform, how do they choose their portfolios, and why do returns vary across stocks for reasons other than risk (Subrahmanyam, 2007). In addition, recent evidence indicates that mergers and acquisitions and capital structure decisions do not conform to rational managers' behavior. Following this, we split this review in three sections: asset pricing and portfolio choice, trading models, and inefficient markets (limits of arbitrage). Behavioral corporate finance is analyzed afterwards.

Campbell (2000) reviews the literature on asset pricing and optimal portfolio choice until then. Modern research interprets that the trade-off between risk and return depends on the behavior of the stochastic discount factor (SDF, pricing kernel) that prices all assets in the economy. The behavior of the term structure of real interest rates restricts the conditional mean of the SDF, whereas the patterns of risk premia restrict its conditional volatility and factor structure. The behavioral models of asset pricing start with Shefrin and Statman's (1994) *Behavioral Capital Asset Pricing Model* (BAPM), which models asset pricing as in CAPM but in a market where noise traders interact with informed traders. Information traders are the ones in the standard CAPM: free of cognitive errors and have mean–variance preferences. Noise traders live outside the CAPM, commit cognitive errors, and do not have strict mean–variance preferences. The expected returns of securities in the BAPM are determined by their 'behavioral betas', that is, the betas relative to the tangent mean–variance efficient portfolio, which is not the market portfolio because noise traders affect security prices.[93]

Hirshleifer (2001) asserts that the purely rational approach to asset pricing is being replaced by a broader psychology-based approach, where security expected returns are determined both by risk

[93] For example, if noise traders prefer growth stocks, this would raise the relative price of growth stock versus value. Thus, the BAPM mean–variance-efficient portfolio would be tilted toward value stocks. However, the estimation of standard and behavioral betas has some problems: we must use imprecise proxies for the true market portfolio, and for behavioral betas the proxy problem is even more severe because the composition of the BAPM mean–variance-efficient portfolio changes over time.

and misvaluation. Daniel, Hirshleifer and Subrahmanyam (2001), for instance, offer a model in which asset prices reflect both covariance risk and misperceptions of firms' prospects, and arbitrageurs trade against mispricing. Authors extending this view include Dean and Faff (2011), who develop a behavioral intertemporal CAPM useful for markets that display the feedback trading phenomenon, Anderson, Ghysels and Juergens (2005), who investigate whether the amount of heterogeneity in analysts' forecasts can explain asset pricing puzzles, and Diether, Malloy and Scherbina (2002), who obtain evidence consistent with the hypothesis that prices reflect optimism. Chordia and Shivakumar (2002), instead, get evidence against this interpretation: momentum strategies might be explained by a set of lagged macroeconomic variables. Shefrin (2008a) summarizes this literature to examine how behavioral finance principles affect asset pricing.

Shefrin and Statman's (2000) *Behavioral Portfolio Theory* (BPT) enhances their BAPM model to determine the mean–variance efficient frontier when investors segregate their portfolios into mental accounts, overlooking the covariances among them. In consequence, the CAPM two-fund separation does not hold in BPT. Goetzmann and Kumar (2008) show younger and less wealthy investors hold under-diversified portfolios, which might suggest they exhibit stronger behavioral biases. Dumas, Kurshev and Uppal (2009) work to identify which portfolio strategies would allow an investor to take advantage of excess volatility and fluctuations in sentiment risk. Finally, Das et al. (2010) generalize Markowitz's mean–variance portfolio theory and Shefrin and Statman's BPT via a unified mental accounting framework. They show that the aggregate allocation across mental accounting subportfolios is mean–variance efficient with short selling, resulting in a fruitful connection between investor consumption goals and portfolio production.

Eventually, these models try to infer whether markets are driven by fundamentals or sentiment. Shefrin (2001b) gives a formal definition of sentiment as a coefficient λ that accounts for either market optimism or pessimism. Then he relates sentiment and asset pricing by stating that the pricing kernel[94] can be decomposed into two stochastic processes: a fundamental process based on aggregate consumption growth that is associated with zero market error, and a sentiment component that reflects the market error. Baker and Stein (2004) build a model that uses market liquidity as a sentiment indicator. They conclude that, in the presence of short-sale constraints, high liquidity would be a symptom that the market is dominated by market sentiment, hence it would be overvalued.

The first trading models to exploit patterns in stock returns were Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999), already mentioned in subsection 3.2.3. Recent extensions are in

[94] The pricing kernel is the stochastic discount factor that prices all assets in the economy (Campbell, 2000): *"In the absence of arbitrage opportunities, there exists a 'stochastic discount factor' that relates payoffs to market prices for all assets in the economy. This can be understood as an application of the Arrow–Debreu model of general equilibrium to financial markets. A state price exists for each state of nature at each date, and the market price of any financial asset is just the sum of its possible future payoffs, weighted by the appropriate state prices"* (p. 1516).

order. Scheinkman and Xiong (2003) show that the interaction of overconfidence and short sale constraints may lead to asset pricing bubbles. Hong, Scheinkman and Xiong (2006) show such phenomena can be exacerbated if assets have limited float. Hong, Kubik and Stein's (2005) model where agents use overly-simplified models to evaluate stocks is able to explain a phenomena like momentum and asset bubbles. Grinblatt and Han (2005) argue loss aversion helps to explain momentum. Kausar and Taffler (2006) provide evidence supporting Daniel et al. (1998). Daniel and Titman (2006) argue that the return predictability of market-to-book ratios (Fama and French, 1992) is driven by overconfidence. Doukas and Petmezas (2007) find support for the self-attribution hypothesis in the market for corporate control. Finally, Vayanos and Wooley (2013) provide an institutional theory of momentum based on flows between investment funds, where flows are triggered by changes in fund managers' efficiency, which investors either observe directly or infer from past performance.

Barberis and Thaler (2003) classify the behavioral models above in three groups, according to which mechanism generates the anomaly: models based on beliefs (e.g., Barberis et al., 1998), models based on institutional frictions —often short sale constraints— combined with mild interpretations of investor irrationality (e.g., Scheinkman and Xiong, 2003), and models based on preferences, like Barberis, Huang and Santos (2001) and Barberis and Huang's (2001) interpretation on narrow framing and changing degrees of loss aversion. Finally, Barberis and Shleifer (2003) analyze the investors' tendency to categorize assets into groups, such as growth and value. Their model generates three empirical predictions. First, style investing generates common factors in asset returns that happen to be grouped in the same style, and that can be accompanied by higher average returns for reasons other than risk. Second, it also increases the correlation between assets in the same style, while it lowers between assets in different styles. Third, the model predicts a rich structure of style return autocorrelations and a high profitability of style momentum and value strategies.

Finally, some models have been offered to explain the limits of arbitrage that would justify why markets are inefficient. Following Subrahmanyam (2007), if financial market prices are driven at least in part by irrational agents, two questions arise. First, why does arbitrage not remove any mispricing? Second, why do irrational traders not get driven out of the market in the long-run? In regards to the first question, Shleifer and Vishny (1997) point two main reasons why inefficiencies may not be arbitraged away, as we mentioned in subsection 3.2.3. The first one is risk arbitrage: based on the concept of noise trader risk (DeLong et al., 1990), they suggest mispricing can go worst before it eventually disappears, so arbitrageurs might have to close or scale back their bets in order to meet margin calls for the short positions in the asset (Scherbina, 2013). Xiong (2001) and Gromb and Vayanos (2002) extend this view. Another source of risk is that the mispricing may disappear because a change in fundamentals. Hence, Daniel et al. (2001) argue that due to risk aversion, arbitrageurs may not be able to remove all systematic mispricing. The second reason why inefficiencies may not be arbitraged away is performance-based arbitrage: an agency problem arises when arbitrage is conducted by specialized agents who manage capital of outside investors. In such case, investors may rationally allocate their money based on past returns of arbitrageurs.

Several models on limits of arbitrage were subsequently proposed. Shleifer and Vishny's (1997) agency model of limited arbitrage shows arbitrage is ineffective when assets are significantly mispriced and arbitrageurs are fully invested. Three consequences follow. First, arbitrageurs' ability to bear against mispricing is limited (they are vulnerable to liquidity constraints and to risks coming from other traders' mistakes). Second, arbitrageurs may bail out of the market when their participation to correct prices is most needed. Third, they will prefer markets with three characteristics: markets where it is easier to estimate fundamental values; markets where investments can be cashed quickly; and, perhaps counterintuitively, markets with lower volatility —the higher the volatility the higher the possibility of losses, and hence the worst for risk averse arbitrageurs. Abreu and Brunnermeier (2003) offer a model with short sale constraints which predicts arbitrageurs, being aware of the existence of an asset bubble, will optimally choose not to short sell the asset and ride the bubble for some time. Brunnermeier and Nagel (2004) provide empirical support to this result: during the dot-com bubble, that was the strategy most hedge funds followed.

In regards to the second question asked before, that is, why irrational traders are not driven out of the market in the long-run, Subrahmanyam (2007) suggests three counter-arguments. First, DeLong et al. (1991) suggest overconfidence may lead irrational agents to bear more risk, which may make them earn a higher return in the long run. Kyle and Wang (1997) offer a similar interpretation. Second, Hirshleifer, Subrahmanyam and Titman (2006) argue that irrational agents who act on sentiment sequentially on the same direction would push up prices. If stock prices influence fundamentals by affecting corporate investment, that would result in the irrationals, as a group, outperforming the rationals. Third, Subrahmanyam argues as well that some investors may trade just for pleasure, as a consumption good. These traders may continue to trade even if they lose money on average.

Behavioral corporate finance. Behaviorist researchers on this area have mainly focused on corporate financial decisions such as capital budgeting, the choice of capital structure, the payment of dividends, and mergers and acquisitions. Stein (1996), on the empirical evidence that CAPM betas are not able to explain cross-sectional stock returns while other variables, such as the book-to-market ratio, do, poses a question: how should one set hurdle rates for capital budgeting decisions? Hence, he offers a new estimator on the assumption that markets are inefficient. Gervais and Goldstein (2004) model a team in which the marginal productivity of a player increases with the effort of others in the team. In such context, an overconfident agent may overestimate her own marginal productivity and work harder, thereby increasing the marginal productivity of her teammates. Similar results are obtained more recently by Gervais, Heaton and Odean (2011).

Traditional finance texts teach that the debt-to-equity choice is a tradeoff between interest tax shields and bankruptcy costs. Baker and Wurgler (2002) suggest instead firms are more likely to issue equity when their stock seems overvalued. In consequence, current capital structure is strongly related to historical market values. Welch (2004) provides empirical evidence that U.S. corporations do not counteract the influence of stock price changes on their capital structures, against rational theories of capital structure. In consequence, the debt-to-equity ratios of these companies vary closely with fluctuations in their stock prices: over five-year horizons, stock returns can explain about 40 percent of debt ratio dynamics. Leary and Roberts (2005) suggest instead that these findings implicitly assume that rebalancing is costless. However, with the presence of adjustment costs, which may make it suboptimal to respond immediately to capital structure shocks, they find firms actively rebalance their leverage to stay within an optimal range. Further insights are provided by Dell'Acqua et al. (2013). Finally, a common result in the corporate finance literature is that firms tend to issue new equity after periods of high stock returns. Alti and Sullaeman (2012) document such behavior only in periods when high returns coincide with strong institutional investor demand.

A behavioral explanation of the dividend puzzle was first given by Shefrin and Statman (1984), as discussed in Section 3.2. More recently, Baker and Wurgler (2004) argue that investors, during certain times, demand higher dividends. They show that the decision of companies to pay dividends is driven by variations in an empirical proxy for such dividend desire. Brav et al. (2005) survey 400 executives to determine the factors that drive dividend and share repurchase decisions. The executives claim that maintaining the dividend payout is as important to them as the firm's investment decisions, while they repurchase stock only when there is residual cash flow after investment spending. Denis and Osobov (2008) find that the propensity to pay dividends is higher among larger, more profitable firms, and those for which retained earnings comprise a large fraction of total equity.

Finally, another classic puzzle is why, in M&A transactions, acquiring firms do not earn superior returns after the takeover, despite the synergistic benefits, while target companies do (Asquith, Bruner and Mullins, 1983). Roll (1986) suggests the hubris hypothesis of corporate takeovers, in which financial markets are rational but corporate managers are not. Shleifer and Vishny (2003), on the contrary, suggest a theory of acquisitions where financial markets are inefficient and some firms are valued incorrectly, while managers are rational, understand stock market inefficiencies, and take advantage of them. Thus, merger transactions would be driven by the stock market valuations of the merging firms: companies with high market valuations would acquire those with low ones. Rhodes-Kropf, Robinson and Viswanathan (2005) and Dong et al. (2006) provide empirical support to the assertion that market misvaluation influences corporate takeovers. Finally, Malmendier and Tate (2008) obtain empirical results closer to Roll's (1986) view: overconfident CEOs overestimate their ability to generate returns and, as a result, overpay for acquired firms.

Behavioral economics. Here the field of analysis is interminable, as it may include areas as diverse as health, public choice, labor markets and others. To make it shorter, in what follows we basically review only some behavioral models on consumption and inter-temporal decision making.

Mullainathan and Thaler (2000) suggest two main areas where the behavioral deviations from the standard economic model —bounded rationality, bounded willpower and bounded self-interest— are more interesting to analyze: namely, financial markets and savings. Savings, in particular, mostly refers to decisions on saving for retirement and the life-cycle model. The behavioral finance tries to explain how the embedded rationality assumptions in the life-cycle model of savings might fail. These assumptions, according to Benartzi and Thaler (2007), are the explicit assumption that savers save and then deplete their savings to maximize some lifetime utility function, and the implicit assumptions that households have the cognitive ability to solve the optimization problem and that they also have sufficient self-control to execute this optimal plan. Then, Benartzi and Thaler (2007) offer a theoretical approach to saving-for-retirement decision making that satisfies the empirical findings previously observed by Benartzi and Thaler (2001). These include a naïve and poor portfolio diversification (they show people often allocate 1/n of their savings amongst n available investment options), lack of self-control and commitment (bounded willpower), mental accounting and framing, and others. In addition, a classic line of research to explain why people fail to save what they need for retirement observes people tend to exhibit excessive discounting of the future due to a present or immediacy bias. Baley, Kumar and Ng (2011) analyze as well some behavioral biases of mutual fund investors, such as attention to news, tax awareness, and familiarity bias. They find biased investors poorly perform due to bad decisions about fund style and expenses, trading frequency, and timing.

Wiener and Doescher (2008) identify the factors that influence people's intention to save for retirement and focus on the role that persuasive communications can play to enhance them. Hershfield et al. (2011) explore how to mitigate lack of self-control by allowing participants in an experiment to interact with realistic computer renderings of their future selves using immersive virtual reality hardware and interactive decision aids. Alternatively, instead of focusing on savings, we may focus on its counterpart: consume. Some efforts have recently been performed to understand consumer decision making. Yoon, Cole and Lee (2009), for instance, analyze the decision making process by older consumers. They identify the notion of fit between individual characteristics, task demands and the contextual environment: when the fit is high, older consumers use their experience to compensate for age-related changes in abilities and resources; when it is low, they feel need to adapt their decision making processes. Mata and Nunes (2010) perform additional research on aging and consumer choice.

Debiasing. A relevant area of research within behavioral economics and finance is the study of strategies for debiasing. If behaviorists have been able to provide empirical evidence that agents and investors tend to make biased decisions, perhaps they might be helpful as well for people to choose better. Rabin (1998) poses a first question about debiasing: do learning and expertise eliminate biases? Rationalists often argue that if economic activity is performed by experts, or the same individuals perform the same tasks repeatedly, full rationality prospers. However, Rabin (1998) reviews the academic literature to argue on the contrary. Kahneman and Tversky (1972) and Tversky and Kahneman (1982b) find that the biasing effects of representativeness are also found in the intuitive judgments of sophisticated psychologists. Kahneman and Tversky (1982c) talk about errors of applications when people do learn about their biases but do not apply this knowledge in subsequent cases. Similar results are in Griffin and Tversky (1992) about overconfidence, who also show learning can even sometimes lead to exacerbate errors. Finally, Hinds (1999) finds experimental evidence that experts may have a cognitive handicap that leads them to be worse predictors of novice performance and to be more resistant to debiasing techniques.

Hence, the study of debiasing techniques and their ability to correct biased choices makes sense. Early research on debiasing, mostly summarized by Kahneman et al. (1982),[95] served to demonstrate the robustness of systematic biases to various corrective measures. Larrick (2004) provides a more recent review. First, he highlights two alternative approaches to 'close the gap' between normative and descriptive decision-making. One approach tries to increase the motivation to perform well. This approach assumes people possess normative strategies and use them when the benefits exceed the costs. The second approach assumes instead that intuitive strategies are imperfect, but may be replaced by strategies that approach normative standards. This is known as prescriptive decision making.

These approaches share a common implication: debiasing requires intervention, since there are many reasons to doubt individuals can debias themselves (Kahneman, 2003b). Several examples of debiasing techniques follow in order. Mahajan (1992) provides experimental evidence that training to reason counterfactually or even providing humbling feedback could help reduce overconfidence. Camerer and Hogarth (1999) show incentives are generally ineffective to reduce biases. Thaler and Benartzi (2001) show firms can rebias employees to save more by changing the status quo and by exploiting mental accounting. Indeed, the effectiveness of changing the status quo to induce others to 'choose right' is behind a whole area of research developed thereafter by Richard Thaler and others, known as libertarian paternalism (Thaler and Sunstein, 2003).

Kahneman and Frederick (2002) suggest some conditions under which biases may disappear, including statistical sophistication, intelligence, manipulations of attention, frequency format, and within-subjects factorial designs. Sanna and Schwarz (2003) test the role of accessibility experiences and attributions in debiasing the hindsight bias. Soll and Klayman (2004) show overprecision to estimate confidence intervals may be reduced by asking judges to generate 10th and 90th percentile

[95] This would include the works by Singer (1971), Dawes (1979), Kahneman and Tversky (1982a), Fischhoff (1982a), and Nisbett et al. (1982).

estimates in separate stages. Lovallo and Kahneman (2003) notice a firm's competitiveness can be seriously damaged if executives actively discourage pessimism —which is often interpreted as disloyalty: *"When pessimistic opinions are suppressed while optimistic ones are rewarded (groupthink theory) an organization's ability to think critically is undermined"* (p. 60). They suggest to take an 'outside view' to remove excess optimism. In the same line, Shefrin and Cervellati (2011) defend that the accident drilling British Petroleum's well in the Gulf of Mexico on 2010 was a result of capital budgeting pitfalls due to biased decision making —affected by excessive optimism, overconfidence, confirmation bias, and aversion to a sure loss. They suggest several debiasing procedures using cognitive repairs (Heath, Larrick and J. Klayman, 1998).

Notwithstanding, some limits of debiasing have been suggested. The strongest critique denies the validity of debiasing in its totality. According to Frankfurter et al. (2004), behavioral finance has taken a marked prescriptive turn with the purpose of remedying deviations from the normative expected utility axioms of rational choice. This view assumes that *"if people do not behave according to the prescriptions of the theory, then something is wrong with people and not with the theory"* (p. 450). In consequence, *irrational* human behavior must be modified. However, Frankfurter et al. (2004) claim against this view: when the limitations of the normative model have become so obvious, it is nonsense to insist upon changing humanity to conform to it. Softer critiques include those by Weinstein and Klein (1995), who find a resistance of personal risk perceptions to debiasing. In particular, they describe four studies regarding health prevention where optimistic biases in perceived risk were found in all studies. The attempts to reduce optimism did not reduce these biases consistently; in contrast, conditions using opposite manipulations often exacerbated the biases. More recently, Kaustia and Perttula (2012) report different debiasing attempts to reduce overconfidence that yield mixed results. First, there are different types of overconfidence (see Chapter 4) and they respond differentially to debiasing. Explicit written warnings, for instance, reduce overplacement. In contrast, they report limited success in reducing miscalibration in probability assessments.

Neuroeconomics. The last area of research to join the behavioral economics and finance is neuroeconomics, which uses knowledge about brain mechanisms to inform economic theory (Camerer, Loewenstein and Prelec, 2004). The foundations of economics were laid in a moment when we did not have access to the human brain. Theories such as expected utility and Bayesian updating assumed rationality of choice and made use of the 'as if' assumption (Friedman, 1953b), assuming people behave as if they use those mathematical tools they derived, sidestepping any psychological detail (Camerer, Loewenstein and Prelec, 2005). The rationality assumption was criticized by some economists already before the emergence of revealed preference, which would show some anomalies in decision making were indeed observed. Now, neuroeconomics allows for a direct measure of feelings and thoughts, allowing scientist to identify whether neural mechanisms produce rational choice and judgment and, if they do not, the brain evidence has the potential to suggest better theory (Camerer et al., 2004).

Camerer et al. (2004, 2005) provide a first insight. Neuroscience uses tools such as brain imaging, behavior of patients with brain damage, animal behavior and recording single neuron activity. Its measurements are challenging our understanding of how people make choices and its implications for economics. First, the brain is composed of multiple systems which interact, and automatic processes which are faster than conscious deliberations and need not follow normative axioms of inference and choice. Second, brain evidence shows emotional activation of some systems in ambiguous choice and strategic interaction, whose design is common to humans and many animals. Third, cognition and affect on one hand, and automatic and controlled processes on the other, work separately, and interact.

Glimcher, Dorris and Bayer (2005) claim these findings place mathematical constraints on existing economic models. Neuroeconomics, indeed, might reconcile the tension between prescriptive and descriptive approaches: when people deviate from rationality it is a physiological encoding of desirability, which Glimcher et al. (2005) name *physiological expected utility*, what leads people' choices. Camerer et al. (2005) set four implications for economics. First, these findings cast doubts on commonly used constructs in economics such as risk aversion, time preference, and altruism. Second, the existence of specialized systems suggests intelligence and bounded rationality are likely to be highly domain specific. Third, brain-scans suggest that money activates similar reward areas as do other primary reinforcers like food and drugs. This would imply that money confers direct utility, rather than being valued for what it can buy as a medium of exchange. Fourth, neuroeconomics challenges the assumed connection between motivation and pleasure.

Camerer (2007) summarizes the areas where rational theories and behavioral economics would better work. Simple kinds of decisions on *life-and-death* (food, sex and danger) do occur as rational theories assume. Instead, classic constructs in behavioral economics such as a preference for immediacy and nonlinear weighting of small and large probabilities are observed. Zak (2011) makes a physiological study of moral sentiments as in Adam Smith (1759). His research provides direct evidence on the brain mechanism, called HOME (human oxytocin-mediated empathy), which produces pro-social behaviors. The HOME circuit permits to identify situations in which moral sentiments will be engaged or not, with applications in areas as diverse as perceived trustworthiness of economic institutions, how moral sentiments can be promoted or inhibited by the firm's environment, and others.

Finally, some criticisms to neuroeconomics have been posed as well. Harrison (2008) argues against some methodological flaws of neuroeconomics and behavioral economics. In particular, his complaints are with the epistemological basis of neuroeconomics research,[96] whose claims would

[96] Epistemology is the study of knowledge claims in philosophy (Harrison, 2008).

appear to build on poor experimental and statistical foundations. Ross (2008) distinguishes two types of research that are both known as neuroeconomics: neurocellular economics (NE) and behavioral economics in the scanner (BES). Harrison's (2008) criticisms of neuroeconomics would not apply to NE but to BES. NE uses constrained maximization and equilibrium analysis to model functional parts of brains. Brains are, like markets, information-processing networks, and NE analyzes the executive systems that govern them. Behavioral economics in the scanner, instead, is the more famous style of neuroeconomics. BES would mainly consist of repeating protocols from behavioral economics experiments while participants are observed under neuroimaging, in order to use brain data to justify arguments for replacing standard microeconomics by notions based on human psychology. Ross (2008) claims this methodology is naively reductionist.

3.4. CONCLUDING REMARKS

Chapter 3 has served as a first approach to the basic research and theories on behavioral economics and finance. To such purpose, we have provided a brief review of the main landmarks of behavioral finance, following a historical approach.

First, after describing some of the early antecedents, we described the main achievements by the researchers that pioneered the behavioral literature. Namely, the prospect theory by Daniel Kahneman and Amos Tversky, the application of psychology to economics by Richard Thaler, the disclosure of the volatility anomaly in financial markets by Robert Shiller, and the first theoretical models by Hersh Shefrin and Meir Statman.

Second, we outlined the main achievements by behaviorist researchers that came to challenge the orthodoxy from the 1980s to the 2000s. These would include the literature on herding, underreaction, the limits of arbitrage, speculative markets, and decision making.

Third, we reviewed some models and theories that behavioral economics and finance have recently provided, in their effort to become an alternative to the academic orthodoxy in areas as diverse as decision theory, financial markets, corporate finance, consumption and inter-temporal decision making, debiasing techniques, and neuroeconomics.

The review of the behavioral literature continues in Part II. Firstly, in Chapter 4, with an extensive insight on the main behavioral biases and anomalies studied in the literature. This would serve for having a better criterion to select which will be the main lines of research in Part III —i.e., the theoretical and experimental research. Secondly, such lines of research will be analyzed in detail in Chapter 5.

PART II. BEHAVIORAL FINANCE: CONCEPTUAL ELEMENTS TO ANALYZE EFFICIENCY IN RETAIL CREDIT MARKETS

SUMMARY OF PART II

Behavioral finance has proved to be a powerful means to highlight anomalies in financial markets and investor decision making. Though it does not imply a global rejection of market efficiency, it does stress the limits of the rationality assumption and the ability to explain phenomena such as return predictability and price bubbles under a behavioral interpretation.

In this thesis we seek to extend the virtues of the behavioral approach to the analysis of informational efficiency in bank-based financial systems —particularly, to the role banks play when granting credit to the economy. Thus, Part II is devoted to provide a deeper insight on the main theories of behavioral economics and finance, theories that will reveal essential to interpret our theoretical and experimental research in Part III. In particular, Chapter 4 reviews the extensive list of biases and anomalies that contradict the efficiency postulates of standard finance. Then, Chapter 5 focuses on two of the most relevant topics within the behavioral literature: namely, overconfidence and prospect theory. Those are the areas we will focus on in our research in Part III, both in the experimental tests (Chapters 7 and 8) and the theoretical models (Chapter 9).

Part II is organized as follows. Chapter 4 is devoted to an extensive research on the main biases and anomalies in the behavioral literature. Then, Chapter 5 focuses the analysis on two areas that will serve as a starting point for our work in Part III; namely, prospect theory and overconfidence.

CHAPTER 4. A TAXONOMY OF BIASES AND ANOMALIES

4.1. INTRODUCTION

This chapter is devoted to provide an extensive review of the main biases and anomalies identified by the literature on behavioral economics and finance. We start providing an original taxonomy that is based on relevant literature. We then focus on an extensive description of the most relevant of those biases and anomalies, as well as a review of the main contributions in the literature about them. Finally, our goal will be to choose, based on the previous analysis, some items on which to focus in Part III. These items will be analyzed more extensively in Chapter 5.

We start providing a taxonomy of biases and anomalies. Kahneman, Knetsch and Thaler (1991) define anomaly as an empirical result that *"is difficult to 'rationalize', or if implausible assumptions are necessary to explain it within the paradigm"* (p. 193). A bias, meanwhile, is a predisposition toward error (Shefrin, 2006). Many authors have provided different taxonomies of the most relevant behavioral biases and anomalies, but rarely using a comprehensive approach. The rules to classify behavioral anomalies are diverse, and different authors often use different names for quite similar concepts —or different anomalies that are closely related— what makes it quite difficult to provide an inclusive classification that satisfies all of them. The taxonomy provided here is based on some relevant works, including Kahneman, Slovic and Tversky (1982), Tversky and Kahneman (1992), Kahneman and Riepe (1998), Rabin (1998), Thaler (1999a,b), Shiller (2000a), Shefrin (2000), Gilovich and Griffin (2002), Barberis and Thaler (2003), Camerer and Loewenstein (2004), and Hens and Bachmann (2008).[97]

---

[97] Kahneman et al. (1982) summarize heuristics and judgmental biases in seven categories: representativeness, causality and attribution, availability, covariation and control, overconfidence, conservatism (multistage evaluation), and judgmental biases in risk perception. Tversky and Kahneman (1992) mention two phases in the choice process —namely, framing and valuation— and list five major phenomena: framing effects, nonlinear preferences, source dependence, risk seeking and loss aversion. Kahneman and Riepe (1998) classify the deviations from rationality in three categories and a consequence. The categories are heuristics (judgmental biases, overconfidence, optimism, hindsight bias and overreaction), errors of preference (prospect theory and loss aversion), and framing. In addition, investment decisions have emotional and financial consequences people must bear —this basically involves regret. Rabin (1998) separates mild biases (reference level and loss aversion, endowment effect, status quo bias), severe biases in judgment under uncertainty (law of small numbers, confirmatory bias, anchoring and adjustment, hindsight bias), and psychological findings that imply a radical critique of the maximizing utility model (framing effects, preference reversals, self-control). Thaler (1999a) cites five market effects: excessive trading volume, excess volatility, equity premium puzzle, preference for dividends, and return predictability. Thaler (1999b) links mental accounting to prospect theory. Shiller (2000a) lists some theories from social sciences used by researchers in finance, like prospect theory, regret and cognitive dissonance, anchoring, mental accounting, over and underreaction, overconfidence, and representativeness. Shefrin (2000) separates heuristic-driven biases (availability, representativeness and gambler's fallacy, anchoring-and-adjustment and conservatism, overconfidence, aversion to ambiguity), frame dependence (related to loss aversion, mental accounting, hedonic editing, self-control, money illusion and regret) and inefficient prices. In the introduction to Gilovich, Griffin and Kahneman (2002), Gilovich and Griffin (2002) identify six general purpose heuristics (affect, availability, causality, fluency, similarity and surprise) and six special purpose heuristics (attribution substitution, outrage, prototype, recognition, choosing

These authors considered,[98] an original taxonomy was elaborated following some considerations. Firstly, we separate psychological biases and the consequences of those biases. In regards to the former, Kahneman (2003a,b) summarizes his work with Tversky in three parts: the heuristics people use and the biases to which they are prone when judging under uncertainty; prospect theory, as a model of choice under risk, and loss aversion in riskless choice; and framing effects. In addition, Tversky and Kahneman (1981) consider two phases in the choice process, an initial of framing and a subsequent of evaluation. While framing might be viewed as a heuristic error —as it implies people are boundedly rational— Rabin (1998) considers framing effects more relevant: more than confusing people, frames may determine a person's preferences. In any case, we must be aware of the very close interrelation between framing and prospect theory that makes them form a natural pair (Barberis and Huang, 2009). Alternatively, other authors (e.g., Barberis and Thaler, 2003) merge prospect theory and ambiguity aversion in a same category (preferences), a line we shall not follow here. In addition, we consider to include a fourth group within biases, which refers to those we make because we are influenced by other people (culture, social contagion, fads, etc.). We denote this group social factors, which refer to cultural and social influences on individual's behavior. Authors highlighting the importance of this group include Shiller (2000a), Shefrin (2000) and Hens and Bachmann (2008), among others.

In regards to the second category, that is, the behavioral consequences that come as a result of our biases in decision-making, we follow Barberis and Thaler (2003) to split them into market anomalies and decision effects ('investor behavior anomalies' in Barberis and Thaler's terminology). To sum up,

---

by liking and choosing by default). Barberis and Thaler (2003) note two kinds of irrationality and two of anomalies. The former includes beliefs (representativeness, conservatism, anchoring, confirmation bias, availability, overconfidence and optimism) and preferences (prospect theory and ambiguity aversion). Anomalies split in market anomalies (e.g., equity premium, excess volatility, return predictability, size effect) and investor behavior anomalies (e.g., naive diversification, excessive trading, disposition effect). Camerer and Loewenstein (2004) separate two categories in decision research: probability judgments (heuristics, availability, representativeness) and preferences (loss aversion, reference dependence, preference reversals, hyperbolic time discounting, framing, anchoring). Hens and Bachmann (2008) distinguish five types of heuristics that lead to anomalies: information selection biases (availability causes overreaction to new information), information processing biases (e.g., representativeness causes gambler's fallacy), decision biases (e.g., mental accounting explains the disposition effect), decision evaluation biases (e.g., hindsight bias) and biases in intertemporal decisions (e.g., hyperbolic discounting).

[98] Some additional authors are in order. Gigerenzer (1991) cites a list of biases, fallacies and errors in probabilistic reasoning (e.g., base-rate fallacy and conjunction fallacy), and explanations of these biases in terms of cognitive heuristics (such as representativeness). Plous (1993) focuses on the social aspects of decision making processes, organized in six sections: perception, memory, and context; how questions affect answers; models of decision making; heuristics and biases; the social side of judgment and decision making; and common traps. Statman (1995) says behavioral finance tries to answer three categories of questions: investor behavior, the interaction of investors in markets (determines security prices), and the interaction of citizens in public policy arenas (determines financial regulations). Belsky and Gilovich (1999) highlight the most relevant biases why people make 'big money mistakes': mental accounting, loss aversion, endowment effect, misconceptions of chance and probability, anchoring and confirmation bias, information cascades and herding, overconfidence, and emotional biases (included in the 2009 edition). Raghuvir and Ranjan Das (1999) classify anomalies in four sections: price and return effects (e.g., return predictability), volume and volatility effects (e.g., excess volatility), time-series patterns (IPO and M&A anomalies) and miscellaneous effects (dividend puzzle, market sentiment). Mullainathan and Thaler (2000) distinguish three ways humans deviate from the standard economic model (bounded rationality, bounded willpower and bounded self-interest). Daniel, Hirshleifer and Teoh (2002) review the systematic errors performed by investors (e.g., loss aversion, excessive trading, portfolio underdiversification, representativeness based on past returns) and analysts (overoptimism and conservatism causing biased and predictable recommendations). Akerlof and Shiller (2009b) highlight five aspects of animal spirits: confidence and feedback mechanisms, attitudes about fairness, the temptation toward corrupt or antisocial behavior, the money illusion, and social contagion. Finally, DellaVigna (2009) offers a classification of deviations from the standard theory in three instances: non-standard preferences, non-standard beliefs, and non-standard decision making.

we differentiate two broad categories, psychological biases and behavioral consequences. On one hand, psychological biases are classified into four groups: heuristics and biases, framing, valuation/errors-of-preference and social factors. Behavioral consequences, on the other hand, may refer to decision effects (related to individuals) or to market anomalies. Table 4.1 provides the basic outline of our taxonomy.

TABLE 4.1 – Schematic taxonomy of biases and anomalies

PSYCHOLOGICAL BIASES	**BEHAVIORAL CONSEQUENCES**
HEURISTICS & BIASES · Heuristics · Judgmental biases	MARKET ANOMALIES · Financial markets · Corporate finance
FRAMING	DECISION EFFECTS
VALUATION / ERRORS OF PREFERENCE · Prospect theory · Intertemporal preferences	
SOCIAL FACTORS	

Source: Own elaboration

In the next sections we analyze some relevant biases and consequences within each category. The remainder of the chapter is organized as follows. Section 4.2 reviews the psychological biases. Section 4.3 does the same with the behavioral consequences. Section 4.4 concludes with some remarks.

4.2. PSYCHOLOGICAL BIASES

The category of psychological biases comprises four groups: heuristics and biases, framing, valuation/errors-of-preference and social factors. In what follows we analyze them in order.

4.2.1. Heuristics and judgmental biases

Heuristics are economical shortcuts for information processing; that is, simple strategies that ignore information (Marewski, Gaissmaier and Gigerenzer, 2010). Information is vast and changes every second, so people develop rules of thumb to make decisions, what often leads them to make some errors (Shefrin, 2000). In its initial conception, heuristics were restricted to the domain of judgment under uncertainty, a scope later broadened (Kahneman and Frederick, 2002) to a variety of domains that share a common process of *attribute substitution*: *"difficult judgments are made by substituting conceptually or semantically related assessments that are simpler and more readily accessible"* (Kahneman and Frederick, 2005, p. 287). Two contrary views among academics are those who defend heuristics are efficient shortcuts for inference and those who do not. On one hand, authors like Gigerenzer and Gaissmaier

(2011) claim heuristics are efficient unless empirically shown otherwise. The concept of *ecological rationality*, as opposite to logical rationality, asks in which situations a given strategy performs better and in which it fails. Thus, no rule is considered to be rational *per se*, or best in all tasks; what matters is to understand when a given heuristic performs better. Marewski et al. (2010) argue we do not need complex cognitive capabilities to make good judgments; instead, it is the simplicity and robustness of human cognition what makes us capable decision makers. Heuristics would be adaptive strategies that evolved in tandem with fundamental psychological mechanisms (Goldstein and Gigerenzer, 2002).[99]

On the other, authors like Kahneman (2003a,b) identify two cognitive systems, reason and intuition, with the latter being the norm. In these dual-process theories (Kahneman and Frederick, 2005), heuristics would be the fast, intuitive, affect-driven and effortless cognitive system, as opposed to the slow, controlled and analytical of reasoning. Heuristics can be powerful and accurate, but when misapplied can cause big mistakes (Hirshleifer, 2008). While judgments are always intentional, intuition generates spontaneous and involuntary impressions that depend on their *accessibility* —i.e., the ease with which thoughts come to mind. Hence, to understand intuition we need to understand why some thoughts are more accessible than others, both in perception and in judgment.[100] Through the process of attribution substitution, a target attribute of the judged object is substituted by a heuristic attribute. However, because the target and heuristic attributes are different, the substitution introduces systematic errors in judgment and decision, known as judgmental biases.

Heuristics and biases specify how agents form expectations, and consequently they are sometimes merged. Nonetheless, most authors consider first the heuristics people use and then the biases they precipitate —for instance, the original approach by Tversky and Kahneman (1974). Thus, the relevant heuristics and judgmental biases are summarized in Table 4.2 and are reviewed below. In particular, we proceed separately with the analysis of each heuristic and the judgmental biases associated to each of them. For better understanding, we proceed in three instances. We start with a review of the three major heuristics introduced by Tversky and Kahneman (1974), representativeness, availability and anchoring-and-adjustment, and the biases related to them. Next, we explain that Kahneman and Frederick (2002) redefine heuristics in terms of the existence of an attribute substitution, and how this implies anchoring is replaced by the affect heuristic. Finally, we analyze some other classic heuristics in the literature, such as overconfidence, optimism, familiarity and others.

---

[99] In addition, much research has been performed to investigate whether and when people rely on heuristics (e.g. Cokely and Kelley, 2009), when do heuristics perform well (e.g. Gigerenzer and Goldstein, 1996) or how accurate they are for predicting uncertain events, such as the performance of stocks on the stock market (Ortmann et al. 2008).

[100] There are two complementary interpretations. On one hand, Tversky and Kahneman (1983) denote *natural assessments* those attributes that are automatically produced, without intention or effort, by the perceptual system or by the intuition. On the other, Kahneman (2003a,b) notes that perceptual systems are designed to enhance the accessibility of changes and differences. Hence, a relevant property of perception is that it is reference-dependent. Just like one feels water at 20ºC fine when weather is cold, and cold when is hot outside, Kahneman and Tversky applied the same idea to construct the experiments about the study of risky choice that led to the formulation of prospect theory.

TABLE 4.2 – Heuristics and judgmental biases

HEURISTIC	JUDGMENTAL BIASES		Related concepts	Notes
AVAILABILITY	ATTENTION ANOMALIES		Overreaction to new info	*Availability causes overreaction to new info (Hens and Bachmann, 2008)*
			Post-earnings announcement drift	*T&K'74, availability, representativeness and anchoring, the 3 basic heuristics*
	HINDSIGHT BIAS	*(overconfidence)*		*Camerer and Loewenstein (2004): availability contributes to hindsight bias* *Fischhoff (1982): hindsight bias explains overconfidence*
REPRESENTATIVENESS	LAW OF SMALL NUMBERS	Gambler's fallacy		*T&K'74: Gambler's fallacy and Law of small numbers, as misconceptions of chance*
		Hot hand fallacy	Momentum and reversals	*Rabin and Vayanos (2010)*
		Extrapolation bias		*Hens and Bachmann (2008): Extrapolation bias is due to representativeness*
	BASE RATE NEGLECT		Cognitive dissonance	*Kahneman and Frederick (2002): base rate neglect and conjunction bias come from Tom W. and Linda experiments of representativeness*
	ILLUSION OF VALIDITY			*Tversky and Kahneman (1974)*
	CAUSALITY AND ATTRIBUTION			*Kahneman et al. (1982)*
	CONJUNCTION &			*Conjunction fallacy is consequence of anchoring in T&K'74, but a consequence of representativeness in Kahneman and Frederick (2002).*
ANCHORING-AND-ADJUSTMENT	DISJUNCTION FALLACIES		Reference points	
AFFECT				*After the 'Anchoring-and-adjustment dispute', anchoring-and-adjustment falls from the heuristics list, to be considered among the 'errors of preference', and affect is included*
	OVERCONFIDENCE	SELF ATTRIBUTION BIAS	Cognitive dissonance	*Daniel et al. (1998) relate self-attribution to cognitive dissonance*
			Under- and overreaction	*e.g., "Overconfidence causes markets to underreact to relevant information, and to overreact to less relevant information" (Odean, 1998b)*
		CONFIRMATION BIAS	Illusion of validity	*Griffin and Tversky (1992) link the illusion of validity to confirmation bias to induce OC*
			Groupthink theory	*Shefrin and Cervellati (2011)*
		ILLUSION OF CONTROL		*Barber and Odean (2002) notice illusion of control increases overconfidence*
		IRRELEVANCE OF HISTORY		*Shiller (2000a)*
	(EXCESSIVE) OPTIMISM		Wishful thinking	*Barberis and Thaler (2003)*
FAMILIARITY	AVERSION TO AMBIGUITY		Status quo bias	*Familiarity explains aversion to ambiguity and the status quo bias (Ackert et al., 2005)*
RECOGNITION HEURISTIC			Endowment effect	*Recognition heuristic (Gigerenzer et al., 1991), fluency heuristic (Marewski et al., 2010)*
FLUENCY HEURISTIC			Home bias, underdiversification	*Huberman (2001): Familiarity causes home country bias*
PRIORITY HEURISTIC				*Cokely and Kelley (2009)*
TAKE-THE-BEST HEURISTIC				*Gigerenzer and Goldstein (1996)*

Source: Own elaboration

A. Availability heuristic

Availability, the most important information selection bias (Hens and Bachmann, 2008), refers to our tendency to estimate the probability of an event by the ease with which occurrences can be brought to mind (Tversky and Kahneman, 1973). Due to limited attention, memory and processing capacities, we make decisions based on subsets of information that are easily available. This is a useful shortcut to assess probability because instances of large classes are usually better recalled, but since availability is affected by factors other than frequency, it leads to several predictable biases (e.g., illusory correlation). Three classic determinants of the availability heuristic are familiarity, salience and imagination.[101]

Early papers include Ross and Sicoly (1977) about egocentric perceptions in availability and attribution, Taylor (1982b) about availability within social psychology, and Kahneman and Tversky (1982b), who identify the simulation heuristic, a mental operation that explains how the availability heuristic works. Availability contributes to attention anomalies (Shiller 2000a), overreaction to new information (Hens and Bachmann, 2008), the hindsight bias, and the curse of knowledge: people who know a lot are not aware of how little others know (Camerer and Loewenstein, 2004). Moreover, Heath, Larrick and Klayman (1998) assert availability effects are ubiquitous: *"A particularly important form of missing information is the absence of experience with highly unusual events. Bank examiners rarely see a bank fail, nuclear technicians rarely see a meltdown, airline personnel rarely witness a crash"* (p. 14).

Attention anomalies – Also known as limited attention (Hirshleifer and Teoh, 2003). Attention is a scarce resource and people's ability to process information is limited, hence before decision making we must select which options to analyze. If the attributes that catch our attention are not critical, attention may lead to suboptimal choices. Barber and Odean (2008) note three indicators of attention for stock investors —recent news about the stock, high price volatility, and abnormal trading volume— and find strong evidence that amateur investors are more likely to buy rather than sell those stocks that catch their attention.[102] Professional investors, instead, would not display the attention-driven buying effect. Odean (1999) suggests attention anomalies, together with overconfidence and the disposition effect, might explain the excessive trading in financial markets. Shiller (2000a) notes attention may be capricious because it is affected by the salience of the object. Hirshleifer and Teoh (2003) show that limited attention to how information is displayed in financial reports may cause investors underreaction to earnings news and explain the post-earnings announcement drift (Bernard and Thomas, 1989).

Hindsight bias – Remembering the past is not straightforward: memories can be lost or distorted, even induce events that never happened (Hoffrage and Hertwig, 1999). Human memory has a limited capacity, so it must work by reconstruction. Hindsight bias results as a side-effect: once we known the

---

[101] See *familiarity* later in this section. *Salience* is the fact that *"colorful, dynamic, or other distinctive stimuli disproportionately engage attention and accordingly disproportionately affect judgments"* (Taylor, 1982b, p. 192).

[102] They suggest as a possible explanation that investors search across thousands of stocks when buying, but only from the few stocks they own when selling —they generally do not sell short.

outcome of an event, our recalled judgments are typically closer to the outcome than our first judgments were (Hoffrage, Hertwing and Gigerenzer, 2000). That is, in hindsight we exaggerate what could have been anticipated in foresight (Fischhoff, 1982b). The availability heuristic contributes to this bias: since events that actually occurred are easier to imagine than counterfactual ones, we tend to overestimate the probability we previously assigned to events that later happened (Camerer and Loewenstein, 2004). One of the most widely studied judgmental bias in risk perception (Rabin, 1998), biases in hindsight would explain overconfidence (Fischhoff, 1982b) and amplified regret (Pan and Statman, 2010).

B. Representativeness heuristic

Tversky and Kahneman (1983) define representativeness as *"the degree of correspondence between a sample and a population, an instance and a category, an act and an actor, or more generally between an outcome and a model"* (p. 295). The idea behind the heuristic is that we infer the probability that an object A belongs to class B, or that it originates from it, by evaluating the degree to which A is representative of B (Tversky and Kahneman, 1974). A tendency to rely on stereotypes, it implies people estimate probabilities based on their beliefs and ignoring the laws of probability (Shleifer, 2000). Kahneman (2003a) and Kahneman and Frederick (2005) embed representativeness in a broader class of *prototype heuristics*, which share the representation of categories by their prototypes as a common psychological mechanism.[103]

Most early research was performed by Kahneman and Tversky —indeed, Kahneman and Tversky's first article (Tversky and Kahneman, 1971) was about the law of small numbers. Kahneman and Tversky (1972) analyze some determinants of representativeness, like the similarity of sample to population and a reflection of randomness, while Tversky and Kahneman (1973) provide experimental evidence of it. Other relevant articles are Bar-Hillel (1982) and Chen et al. (2007). In addition, several models use this heuristic. For instance, Barberis, Shleifer and Vishny (1998) suggest investors, in forecasting future earnings, interpret recent past earnings using the heuristic, and Gennaioli and Shleifer (2010) provide a memory-based model of probabilistic inference. Finally, representativeness leads to several biases of judgment under uncertainty. Tversky and Kahneman (1974) mention insensitivity to prior probability of outcomes (a.k.a. the base rate neglect), insensitivity to sample size, misconceptions of chance (which includes the law of small numbers and the gambler's fallacy), insensitivity to predictability, illusion of validity, extrapolation bias, and misconceptions of regression. In addition, the gambler's and hot hand fallacies have been suggested to cause both over and underreaction (Rabin 2002a). We see them next.

[103] Kahneman and Frederick (2002) notice two uses of the word representative until then: first, a prototype (a representative exemplar) is used to represent categories; second, the probability of an object belonging to a category is judged by the degree the object is representative of the category. Thus, representativeness involves two separate acts of substitution —the prototype instead of the category, and the heuristic attribute of representativeness instead the target attribute of probability. Now, they describe the prototype heuristics when a prototype is substituted for its category, but where representativeness is not necessarily the heuristic attribute. Base-rate neglect, scope neglect and duration neglect would also fall in this category.

Law of small numbers – People have strong intuitions about random sampling. One of them is that they tend to exaggerate how closely a small sample will resemble the parent population (Tversky and Kahneman, 1971). A bias related to representativeness and to the tendency to under-use base rates (Tversky and Kahneman, 1974), the law of small numbers leads to gambler's fallacy and misperception of regression to the mean (Rabin, 1998), and a belief in the hot hand fallacy. Rabin (2002b) develops a model alleged to be a plausible explanation for the empirical finding in stock markets of short-term underreaction but medium term overreaction to announcements.

Gambler's fallacy – A consequence of misconceptions of chance, the gambler's fallacy is a judgmental bias caused by representativeness (Tversky and Kahneman, 1974) that implies the mistaken belief that random sequences should exhibit systematic reversals (Rabin and Vayanos, 2010) and a tendency to see patterns in truly random sequences (Barberis et al., 1998).

Hot hand fallacy – Related to the law of small numbers and to representativeness, the fallacy appears when an individual predicts long streaks of similar signals will continue (Rabin and Vayanos, 2010). Similar to the gambler's fallacy in the sense that it implies a failure to appreciate statistical independence, the hot hand fallacy involves instead the belief in an excessive persistence rather than reversals. Nonetheless, some authors suggest the hot hand fallacy may arise as a consequence of the gambler's fallacy (e.g., Rabin, 2002b). Both fallacies would explain some financial puzzles, such as momentum and reversals in asset returns (Rabin and Vayanos, 2010). In addition, the hot hand fallacy is related to the hot hands effect (Hendricks, Patel and Zeckhauser, 1993) cited in Chapter 2.

Extrapolation bias – Caused by representativeness, the extrapolation bias suggests people bet on trends (Shefrin, 2000). Tversky and Kahneman (1973) provided first experimental evidence, while alleged empirical evidence includes Benartzi (2001), who shows employees tend to buy stocks of the company for which they work for after prices had already gone up. Its presence may lead to either overreaction or underreaction.

Base rate neglect – Tversky and Kahneman (1974) noticed that prior probabilities (i.e., base-rate frequencies) play a relevant role in probability estimation but have no effect on representativeness. This implies a base rate neglect (a.k.a. base rate fallacy or base rate bias): an insensitivity to prior probability of outcomes. Prendergast and Stole (1996) relate it to cognitive dissonance reduction: individuals overweight their own information to the detriment of others. Although it received the most attention in social psychology among all cognitive illusions (Gigerenzer, 1991), the base rate neglect remains a controversial bias. First, the neglect of base rates seems in direct contradiction to the widespread belief that judgments are unduly affected by stereotypes (Landman and Manis, 1983). Second, a relevant source of controversy refers to the debate, already acknowledged, between Kahneman and Gigerenzer about whether heuristics are efficient shortcuts or not. In particular, Tversky and Kahneman (1982a) obtained experimental evidence on the impact of base-rate data using questions of the type (p. 154):

> If a test to detect a disease whose prevalence is 1/1000 has a false positive rate of 5%, what is the chance that a person found to have a positive result actually has the disease, assuming you know nothing about the person's symptoms or signs?

Students at Harvard Medical School answered this medical diagnosis problem, half of them judged the probability that the person actually had the disease to be 0.95, average answer was 0.56, and only 18% of participants responded 0.02, the correct answer. However, Cosmides and Tooby (1990) rephrased the medical diagnosis problem in a frequentist way to find the Bayesian answer 'one out of 50' was given by 76% of the subjects: the base-rate fallacy disappeared. Kahneman and Tversky (1996) reply they ignore critical evidence that judgments of frequency are susceptible to systematic biases.

Illusion of validity – People tend to select the outcome that is most representative of the input, and in doing so the confidence they have in their prediction depends on the degree of representativeness with no regard to the factors that limit predictive accuracy (Tversky and Kahneman, 1974). A sort of confirmation bias leading to overconfidence (Shefrin, 2000), the illusion of validity tends to persist even when we are aware of the factors that limit the accuracy of our predictions. Einhorn and Hogarth (1978) suggest we exhibit the bias because we search for confirming evidence (see *confirmation bias*).

Causality and attribution – When people attempt to infer the causes for the effects observed, they may make mistakes related to salience, availability, representativeness, egocentric biases and many others. The early research on causality and attribution is summarized in Kahneman et al. (1982), including Nisbett et al. (1976), Tversky and Kahneman (1980), Tversky and Kahneman (1982a) and Ross and Anderson (1982). The bias extends to groups as well, causing *xenophobia* (Hirshleifer, 2008).

Conjunction and disjunction fallacies – A conjunction fallacy appears when people believe the probability of a conjunction of two events is greater than that of one of its constituents. Related to it is the disjunction fallacy: the probability of an event A must be equal to the total probability of all events whose union is equal to A, but experimental subjects often underestimate the probability of residual hypotheses. Gennaioli and Shleifer (2010) offer a model able to explain both fallacies. An antecedent to these studies on conjunction and disjunction fallacies is Bar-Hillel (1973):[104] However, the conjunction fallacy is original of Tversky and Kahneman (1982b), which includes the classic *Linda experiment* (here reported as in Tversky and Kahneman (1983), p. 299):

> Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in antinuclear demonstrations. Which of this two alternatives is more probable:
>
> Linda is a bank teller (T)
> Linda is a bank teller and is active in the feminist movement (T&F)

[104] In this study, subjects chose whether to participate in three types of events: (i) simple, like drawing a red marble from a bag with 50% red marbles; (ii) conjunctive, like drawing a red marble seven times in succession, with replacement, from a bag with 90% red marbles; and (iii) disjunctive, like drawing a red marble at least once in seven successive tries, with replacement, from a bag with 10% red marbles. Most preferred the conjunctive (p = .48) rather than the simple event (p = .50), and the simple rather than the disjunctive event (p = .52).

Most respondents answer T&F when the (obvious) correct answer is T. We must mention we have included the conjunction and disjunction fallacies as an alleged consequence of the representativeness heuristic. However, that is not the original view. Tversky and Kahneman (1974) suggest both fallacies are induced by anchoring: the stated probability of the simple event provides a natural starting point to estimate the probabilities of both conjunctive and disjunctive events. Later, Tversky and Kahneman (1983) would suggest them to be a consequence of representativeness: judgments are based on the match (similarity, representativeness) between the description of Linda and the two alternatives. This change in interpretation is related to the concept of attribution substitution, eventually developed by Kahneman and Frederick, 2002), and the debate it generated about whether anchoring-and-adjustment is a heuristic or not. In what follows we delve into the concept of attribution substitution and the debate on anchoring-and-adjustment as an aside.

Aside: Attribution substitution and the debate on Anchoring-and-adjustment

The article that defined the heuristics and biases approach (Tversky and Kahneman, 1974) included anchoring-and-adjustment as one of the three basic general-purpose heuristics (the others being representativeness and availability).[105] They describe it as follows: *"people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient"* (p. 1128). For instance, their classic wheel-of-fortune experiment (see subsection 3.2.2) would be an example of a reference point given by the formulation of the problem. However, Kahneman and Frederick (2002) would later introduce attribution substitution and remove anchoring from the list of the essential heuristics. Attribution substitution is an underlying psychological process that explains how representativeness, availability and other heuristics and biases operate: people often try to solve a difficult question by answering an easier one instead, usually being unaware of the substitution. Through this process, judgment is mediated by a heuristic when we assess a *target attribute* of an object by substituting another property of that object, the *heuristic attribute*, which comes easier to mind (e.g., representativeness replacing probability). Moreover, the process is not restricted to the domain of judgment under uncertainty, unlike in the early work of Kahneman and Tversky.

This change in understanding the process of how heuristics work modified the list of heuristics in consequence. First, attribute substitution is implied in some classic articles, like Kahneman and Tversky (1973) on the base rate neglect and the conjunction/disjunction fallacies (Kahneman, 2003a). Second, it led to the introduction of new heuristics such as the *affect heuristic* (Finucane et al., 2000): affect is a natural assessment, automatically computed and always accessible, so the basic evaluative attribute (e.g., good/bad, like/dislike) is a candidate for substitution in any task that calls for a favorable or

[105] Slovic and Lichtenstein (1971) must be reckoned here as an antecedent to the study of anchoring.

unfavorable response. Third, Kahneman and Frederick (2002) note anchoring does not fit the definition of a judgment heuristic anymore, *"because it does not work through the substitution of one attribute for another, but by increasing the plausibility of a particular value of the target attribute"* (p. 54). Thus, they suggest anchoring should be replaced by the affect heuristic in the list of major heuristics. Ever since, most authors (e.g., Camerer and Loewenstein, 2004) classify anchoring-and-adjustment as an *error of preference* that derives from the existence of reference points (see Table 4.4). Indeed, reference points play a determinant role in determining how people anchors their beliefs to a given level and then make inferences from there to adjust their initial guess.[106]

C. Affect heuristic

The third of the major-purpose heuristics was introduced by Finucane et al. (2000), who suggest people rely on affect —i.e., the specific quality of goodness or badness- when judging risks and benefits of specific hazards. Representations of objects and events in our minds are tagged to varying degrees with affect. Then, the affect heuristic would be the reliance on such feelings to make judgments, which may provide faster and more efficient intuitions than retrieving from memory some relevant examples. The failure to identify the affect heuristic, say Kahneman and Frederick (2002), *"reflects the narrowly cognitive focus that characterized psychology for some decades. There is now compelling evidence that every stimulus evokes an affective evaluation"* (p. 55), conscious or not.

Finucane et al. (2000) obtain experimental evidence that the observed negative correlation between risk and perceived benefit is stronger if time pressure, designed to increase reliance on affect, is introduced. In consequence, Loewenstein et al. (2001) propose an alternative theoretical perspective to all cognitive theories of choice under risk to date, the so-called model of risk-as-feelings. The model emphasizes the role affect plays in decision making: beliefs about risk would be expressions of emotion that often diverge from cognitive assessments. Slovic et al (2002) introduce a theoretical framework for affect, and show it to be the heuristic attribute for numerous target attributes, in common with the model of risk-as-feelings by Loewenstein et al. (2001).

D. Overconfidence

Overconfidence, the human tendency to overestimate our own skills and predictions for success (Ricciardi and Simon, 2000), is a classic in the field. Indeed, most academic reviews include it as one of the most relevant heuristic-driven biases. It entails a miscalibration of subjective probabilities. Following Lichtenstein and Fischhoff (1977), a judge is said to be well calibrated if *"over the long run,*

[106] The concept of attribution substitution contributed as well to develop *heuristic elicitation*. Traditionally, heuristics were studied by examining biases from normative rules, but attribution substitution permits to apply more direct tests: a heuristic elicitation can be designed such that one group of respondents judge a target attribute for a set of objects, while another evaluates the hypothesized heuristic attribute. Measured in comparable units (e.g., percentiles), we prove the use of a heuristic if both results are identical. Following this, Kahneman and Frederick (2005) present an attribute-substitution model of heuristic judgment where difficult questions are tackled by answering to an easier one, and introduce a research design for studying attribute substitution.

for all propositions assigned the same probability, the proportion true is equal to the probability assigned" (p. 161). However, researchers like Oskamp (1965), Alpert and Raifa (1969), Fischhoff, Slovic and Lichtenstein (1977) and Lichtenstein, Fischhoff and Phillips (1982) showed people use to be poorly calibrated, and later research only confirmed the results —surveys include Rabin (1998) and Griffin and Brenner (2004). However, the study of overconfidence is not so straightforward since it may refer to different concepts. Moore and Healy (2008) provide a reconciliation of the three different uses. First, a person may be overconfident in estimating her own performance —named *overestimation*. Interestingly, overestimation seems not to be universal: people are overconfident when estimation involves hard tasks, but underconfident when it involves easy tasks —contrariwise if they have placed themselves in such tasks. Second, a person might be overconfident in her own performance relative to others. They call this *overplacement*, also known as the 'better-than-average' effect (Williams and Gilovich, 2008; Grieco and Hogarth, 2009). Third, people may exhibit an excessive precision to estimate future uncertainty (e.g., Alpert and Raiffa, 1969), this one known as *overprecision*.

Koriat, Lichtenstein and Fischhoff (1980) suggest overconfidence is caused by a *confirmation bias*: after one alternative is chosen, people look for information that confirms the answer, but not that could falsify it. In Gigerenzer's (1991) words, *"the mind is not a Popperian"* (p.4) and this selective information search artificially increases confidence. Researchers suggest men are more overconfident than women. Lundeberg, Fox and Punccohar (1994) show men are more overconfident particularly in tasks that are perceived to be masculine —this would include financial topics (Prince, 1993). Barber and Odean (2001) test it and find men trade more frequently and exhibit more losses.[107] Barber and Odean (2002) suggest the bias explains why investors who switched from phone-based to online trading in the 1990s traded more speculatively and less profitable since then. Biais et al. (2005) find experimental evidence of subjects with greater judgmental overconfidence performing worse as a trader. Recent tests include Grinblatt and Keloharju (2009) on equity trading, Grieco and Hogarth (2009) on overestimation and overplacement, Williams and Gilovich (2008) on the better-than-average effect, and Chen et al. (2007) on cultural differences: Chinese investors hold fewer stocks, but trade more often than Americans.

The boom in overconfidence research within behavioral finance would come in the 1990s. Daniel, Hirshleifer and Subrahmanyam (1998) were perhaps the first to note the importance of this bias in financial markets with their theory of under and overreaction based on investor overconfidence and biased self-attribution. Odean (1998b) considers the increase of the expected trading volume the most robust effect. Odean (1999) and Statman, Thorley and Vorkink (2006) test such hypothesis with partial positive results. Scheinkman and Xiong (2003) offer a model that uses overconfidence to explain the generation of asset bubbles. In regards to corporate finance, the research on managerial overconfidence

[107] They find men trade 45% more than women thereby reducing their returns more than women do (-2.65% a year versus -1.72%). The differences are even higher between single men and single women (single men trade 67% more and see their returns reduced by 1.44% a year compared to women). Barber and Odean attribute the results to overconfidence.

is a classic as well. Camerer and Lovallo (1999) explore whether the observed high rates of business failure are caused by an excessive business entry due to overconfidence and optimistic biases.[108] Malmendier and Tate (2005a,b) obtain similar results linking managerial overconfidence to the high rates of corporate merger and acquisition. Additional research may be found in surveys by Shefrin (2006) and Baker, Ruback and Wurgler (2007).

Daniel, Hirshleifer and Subrahmanyam (2001) suggest there is rationale to think *"overconfidence may have evolved under natural selection as a way to promote genetic reproduction"* (p.922). Training to reason counterfactually or even providing humbling feedback could help reduce the bias (Mahajan, 1992), yet overconfidence may have pervasive effects through several biases and anomalies it is related to. For instance, Pan and Statman (2010) note overconfident investors are likely to overstate their risk tolerance. Hirshleifer (2001) and Barberis and Thaler (2003) confirm overconfidence has been alleged to explain return predictability, excess volatility and excess trading, the forward premium puzzle (Burnside et al., 2011), and sensation seeking (Grinblatt and Keloharju, 2009). Finally, Keren (1987) and Griffin and Tversky (1992) suggest ambiguity of evidence is an important mediating factor in both overconfidence and confirmation bias. Some of these biases are analyzed next.

Self-attribution bias – Attribution theory (Bem, 1965) asserts individuals tend to attribute to their high ability those events that confirm the validity of their actions, while evidence against it is attributed to external noise or sabotage. Daniel *et al.* (1998) relates this to the notion of cognitive dissonance, in which individuals internally suppress information that conflicts with past choices. Some anomalies are attributed to be a consequence of a biased self-attribution. Daniel *et al.* (1998) suggest this bias can promote feedback to cause over and underreaction, and Shiller (2003) follows them to assert that the effect of self-attribution in the spread of *stories* is essential in the formation of speculative bubbles. Statman et al. (2006) observe the impact of self-attribution bias on investor's overconfidence when they find some investors become more (less) overconfident about the goodness of active trading when they have experienced positive (negative) portfolio returns.

Confirmation bias – A departure from Bayesian rationality where subjects, once they formed a strong hypothesis, attach too much importance to news that support their views while they are inattentive to new information that might contradict them (Rabin, 1998; Shefrin, 2006). It is a form of anchoring in some way: people tend to accept confirming evidence for their initial positions (Lord, Ross and Lepper, 1979). The bias does not necessarily imply people *misinterpret* additional evidence, but that they *ignore* it (Bruner and Potter, 1964) or, even worst, that they tend to misread evidence as additional

[108] Overconfidence causing excessive business entry was already in the hubris hypothesis by Roll (1986), but Camerer and Lovallo (1999) were the first to test it experimentally. They set some entry games in which the entrants' payoffs sometimes were random and others they were told in advance to depend on their own skill, and find evidence of an overconfidence effect on business entry and that self-selection makes the effect stronger. This last result made authors suggest a *reference group neglect*: self-selected subjects seem to neglect they are competing with a group of subjects who all think they are skilled too.

support for their hypothesis (Rabin and Schrag, 1999). Empirical tests of confirmation bias include Lord et al. (1979) on capital punishment, Darley and Gross (1983) on the influence of background information and Plous (1991) on safety of nuclear technology. Griffin and Tversky (1992) and Rabin and Schrag (1999) link the illusion of validity to confirmation bias to induce overconfidence. Stiglitz (2012) says equilibrium fictions may appear because the only pieces of evidence people see are those in accordance with their convictions. This would lead to social rigidity (Hoff and Stiglitz, 2010, 2011): in social sciences convictions may affect reality —a phenomenon coined reflexivity by Soros (2010). Indeed, groupthink is a form of collective confirmation bias (Shefrin and Cervellati, 2011). Thus, since convictions change slowly due to confirmation bias, collective actions, political actions included, change slowly. This might explain the existence of very different belief systems and cognitive frames across societies.

Illusion of control – Langer (1975) defines the illusion of control as people behaving as though chance events were subject to their control. That is, we judge an outcome as a consequence of our acts when in fact we have been simply lucky. Ji, Nisbett and Su (2001) find Americans believe in stability of events so they think things are more predictable than they really are, what would explain why Americans exhibit illusion of control, as reported in Presson and Benassi (1996) and others.

Irrelevance of history – According to Shiller (2000a), a common kind of overconfidence is the tendency to perceive history as irrelevant: history would not be a guide to the future, which must be judged only using factors we see now. This effect discourages taking lessons from history and statistics.

E. (Excessive) Optimism

Kahneman and Riepe (1998) declare optimists those who underestimate the likelihood of bad outcomes over which they have no control. Shefrin (2006) says they both overestimate how frequently they will experience favorable outcomes and underestimate unfavorable ones. A classic topic of research on excessive optimism are firms' executives, whose overoptimism would be a result of both cognitive biases (e.g., anchoring) and organizational pressures, when not of hubris. They often fall victim of what psychologists call the planning fallacy: they make decisions based on excessive optimism instead of a rational evaluation of gains, losses and probabilities, they exaggerate benefits and underestimate costs, and overestimate scenarios of success while overlooking the potential for mistakes and miscalculations, setting themselves for a future failure (Lovallo and Kahneman, 2003). Large capital investments, M&As and efforts to access new markets are classic situations where optimism pervade managers decisions, explaining the high rates of failure observed.

Cowen, Groysberg, and Healy (2006) provide a measure of forecast optimism by market analysts, and suggest that trading incentives affect their optimism bias. Lovallo and Kahneman (2003) observe that the competitiveness of a company may be seriously damaged if executives actively discourage pessimism among their employees —often interpreted as a sign of disloyalty. Overoptimism is related to biases such as self-attribution (Lovallo and Kahneman, 2003), overconfidence, groupthink theory, wishful thinking (Barberis and Thaler, 2003), and others.

F. Familiarity

The familiarity bias is related to the evidence that people fear change and the unknown (Cao et al., 2011). Ackert et al., 2005 find experimental evidence that familiarity is a key determinant of investment behavior. It helps to explain biases and anomalies like ambiguity aversion and status quo bias (Ackert et al., 2005), recognition heuristic (Gigerenzer, Hoffrage and Kleinbölting, 1991), fluency heuristic (Marewski et al., 2010), and decision effects like the endowment effect, portfolio underdiversification, and home and local biases (Cao et al., 2011). For instance, Huberman (2001) explains the home and local biases as people simply preferring to invest in the familiar. The decision effects are analyzed in detail in subsection 4.3.2. Aversion to ambiguity and recognition heuristic, instead, are reviewed in what follows.

Aversion to ambiguity – Ambiguity is the uncertainty about uncertainties (Einhorn and Hogarth, 1986).[109] Then, the aversion to ambiguity describes a preference for known over unknown risks —as demonstrated in the Ellsberg paradox.[110] The paradox suggests people behave differently when they are given objective probabilities than when they are not and, since ambiguous situations are typical in financial markets, ambiguity aversion is expected to have relevant effects there. Early papers include Fellner (1961), who introduced the concept of decision weights. Epstein and Schneider (2010) review models of ambiguity aversion and their implications for portfolio choice and asset pricing. Nonetheless, the opposite result —people preferring ambiguous alternatives— may be found in some circumstances. Einhorn and Hogarth (1986) develop a descriptive model of judgment under ambiguity that specifies conditions for ambiguity seeking and avoidance, whereas Roca, Hogarth and Maule (2006) show that the status quo bias could lead to ambiguity seeking, when individuals in various experiments preferred not to exchange an ambiguous alternative in their possession for an unambiguous one.

Recognition heuristic – Two processes govern the use of the recognition heuristic, recognition and evaluation. Recognition is the capacity to make inferences in cases of limited knowledge (Goldstein and Gigerenzer, 2002): *"If one of two objects is recognized and the other is not, recognition heuristic infers that the recognized object has the higher value with respect to the criterion"* (p. 75). Evaluation judges its ecological rationality: the heuristic will be ecologically rational if the recognition validity for a given criterion is substantially higher than chance ($\alpha > .5$). Recognition is the most frugal of all heuristics (Goldstein and Gigerenzer 1999), allowing people to benefit from ignorance by making inferences from patterns of missing knowledge. It was explicitly proposed as a model of inferences made from memory

[109] Einhorn and Hogarth (1986) suggest payoffs can, in the presence of ambiguity, affect the weight given to uncertainty, making real probabilities more ambiguous than the exact probabilities of gambles.

[110] The Ellsberg paradox shows people tend to prefer a lottery *A*, where a ball is picked at random from an urn with 50 red and 50 black balls, to a two-stage lottery *BC*, where first a coin is flipped and then either urn B (80 red, 20 black balls) or urn C (20 red, 80 black) is used to pick up a ball at random —however, both lotteries have a 50% chance of winning (Thaler, 1983).

—as opposed to inferences from givens, where cue values are provided by the experimenter (Gigerenzer and Goldstein, 1996). Similarly, Schooler and Hertwig (2005) pose the notion of beneficial forgetting: loss of information aids inference heuristics that exploit mnemonic information. In addition, recognition heuristic is related to familiarity, since it implies a probabilistic cue (Gigerenzer et al., 1991).

Gigerenzer and Goldstein (2011) compile the literature over a decade. Goldstein and Gigerenzer (1999) provide experimental evidence of people using the heuristic. Goldstein and Gigerenzer (2002) identify the conditions under which the recognition heuristic leads to efficient results due to a *less-is-more* effect: when ignorance is systematically rather than randomly distributed, recognition and criterion are correlated, so the heuristic leads to successful results. The correlation between recognition and criterion can be learned from experience or can be genetically coded. Finally, Ortmann et al. (2008) analyze how the heuristic performs in portfolio management to beat the market, finding mixed results.

Fluency heuristic – The recognition heuristic is binary, that is, an alternative is either recognized or not, so it does not help when two alternatives are recognized but one more strongly than the other. Fluency heuristic fills the gap: if one alternative is recognized faster than another, the fluency heuristic infers the one that has the higher value on the criterion (Schooler and Hertwig, 2005).

G. Other heuristics

Priority heuristic – According to the priority heuristic, decisions between sure versus risky options are the result of considering simple reasons for a decision in a fixed order, until a stopping rule is met (Cokely and Kelley, 2009). Rieger and Wang (2008b) see it as an alternative model to the best 'as-if' models of decision under risk, including cumulative prospect theory.

Take-the-best heuristic – This heuristic considers cues sequentially in the order of their validity (Gigerenzer and Goldstein, 1999), where validity is the probability that an alternative has a higher value on a criterion than another (Marewski et al., 2010).

4.2.2. Framing

The second group in the category of psychological biases consists of framing and the biases related to it. Behaviorists have shown agents do not make their choices in a comprehensively inclusive context as the rational-agent model predicts. In particular, an essential aspect of rationality is invariance: preferences are not affected by inconsequential variations in the description of outcomes (Kahneman, 2003a). However, invariance is violated in framing, because alternative descriptions lead to different choices only by altering the salience of different features of the problem. Framing effects include a variety of biases related to two classics in the literature: frame dependence and mental accounting. This way, decision making would be better characterized by narrow framing (Kahneman and Lovallo, 1993) and the related notions of mental accounting (Thaler, 1985) and choice bracketing (Read, Loewenstein and Rabin, 1999), among others. They are summarized in Table 4.3 and reviewed in detail below.

TABLE 4.3 – Framing

FRAMING BIASES		Related concepts	Notes
FRAME DEPENDENCE	Narrow framing	Equity premium puzzle	*Narrow framing & Equity premium puzzle: Barberis and Huang (2007)*
		Loss aversion	*Tversky and Kahneman (1986)*
		Money illusion	*Narrow framing & Money illusion: Kahneman et al. (1986a)*
	Context effects		*Simonson and Tversky (1992)*
	Repeated gambles		*Repeated gambles, see Kahneman and Riepe (1998)*
MENTAL ACCOUNTING	Hedonic editing	House money effect	*House money effect: Hens and Bachmann (2008)*
		Self-control	*Thaler and Shefrin (1981)*
	Choice bracketing		*Choice bracketing (Read et al. 1999)*

Source: Own elaboration

A. Frame dependence

The antecedent of frame dependence is the isolation effect by Kahneman and Tversky (1979): people tend to discard elements shared by all prospects, focusing only on those that distinguish them. This led to the concept of framing (Tversky and Kahneman, 1981): *"the decision-maker's conception of the acts, outcomes and contingencies associated with a particular choice"* (p. 453), which may produce predictable shifts of preference when the same problem is framed differently. It results that the most accessible features influence decisions while those of low accessibility are ignored. Thus, the way a prospect is posed will affect the eventual choice —a result known as frame dependence. The passive acceptance of the formulation given is a basic principle: two logically —but not transparently— equivalent statements of a problem lead decision makers to choose different options (Rabin, 1998). Some concepts closely related are narrow framing, context effects, repeated gambles and hedonic editing. We see them next.

Narrow framing – Narrow framing (Kahneman and Lovallo, 1993) is the tendency to analyze problems in a specific context without reflection of broader considerations (Hirshleifer and Teoh, 2003). Hence, people evaluate risks in isolation, apart from other risks they are already facing (Barberis and Huang, 2009). Kahneman (2003a,b) interprets framing in terms of accessibility: narrow framing occurs because decisions are made through intuition instead of effortful reasoning. Several models incorporate narrow framing. Barberis, Huang and Santos (2001) extended asset pricing to a framework where investors derive utility not only from consumption, but from stock market fluctuations too. Then, Barberis and Huang (2009) improve that model with an intertemporal preference specification that incorporates framing into standard preferences: the utility function depends directly on the outcome of a gamble and indirectly on the gamble's contribution to wealth. The specification is shown to be tractable in partial equilibrium —allowing to analyze portfolio and consumer choice— and in equilibrium —allowing to study the effect of narrow framing on asset prices. Barberis, Huang and Thaler (2006) and Barberis and Huang (2007) apply a similar model, the former to account for the stock market participation puzzle and the latter to study the equity premium puzzle.

Framing has been related to several biases and anomalies. Narrow framing may be a result of taking regret into account in utility functions (Barberis and Huang, 2009). Kumar and Lim (2008) say that active intra-day investors tend to exhibit a weaker disposition effect, because they are more likely to think about portfolio-level outcomes. Framing influences loss aversion and diminishing sensitivity: a frame that highlights losses makes a choice less attractive, whereas if it makes losses small relative to the scales involved it exploits diminishing sensitivity, making the choice more attractive (Tversky and Kahneman, 1986). In addition, money illusion is an effect derived from framing (Kahneman, Knetsch and Thaler, 1986a). Other related concepts are analyzed in what follows.

Context effects – Context effects refer to situations where a subject's preferences among options depend on which other options are in the set (Camerer and Loewenstein, 2004). Thus, adding or subtracting options in a menu of choices may affect the proportion of consumers who choose one of the existing options. Simonson and Tversky (1992) provide examples that the menu of choices influences people's decisions. Rabin (1998) identifies it as one of the elicitation effects, together with framing effects and preference reversals.

Repeated gambles – Statistical aggregation reduce the relative risk of a series of gambles. Kahneman and Riepe (1998) show that, when people are asked these two questions…

#1 What is your cash-equivalent for one play of the following gamble: 50% chance to win $1,000, or a 50% chance to win nothing.

#2 What is your cash-equivalent for five plays of the following gamble: a 50% chance to win $1,000, or a 50% chance to win nothing.

…most people set a cash equivalent more than five times higher for #2 because, due to statistical aggregation, the second proposition is relatively less risky. However, if asked…

#3 You are offered one play of the gamble: a 50% chance to win $1,000, or a 50% chance to win nothing. More opportunities to play this gamble may be available later. What is your cash equivalent for the present opportunity?

…a decision-maker who frames options narrowly will not distinguish between #1 and #3, setting the same cash-equivalent. This fails to take advantage of reduced risk in repeated gambles due to statistical aggregation: they behave as if the current decision problem was the last one they will ever made.

Hedonic editing – A concept related to frame dependence and mental accounting, hedonic editing refers to the evidence that people code combinations of events in a way it make them as happy as possible (Thaler, 1999b). Under a framing interpretation (e.g., Shefrin, 2000), investors may choose to interpret problems in a way, for instance, they seem to be able to avoid a loss.[111] Alternatively, Thaler and Johnson (1990) suggest a theory of hedonic editing where people organize their mental accounts in a way that makes them feel better.

[111] An example is the advice by stockbrokers to their costumers to *transfer their assets* to a position currently recommended, instead of recommending to *sell* an asset previously recommended that now quotes at a loss.

B. Mental accounting

Closely related to framing, mental accounting refers to the implicit methods individuals use to code and evaluate transactions, investments, gambles, and other financial activities (Kahneman and Tversky, 1984; Thaler, 1985). Through this process, people keep track of and evaluate their transactions, like financial accounting in firms (Thaler, 2008). Shiller (2000a) calls it *mental compartments* and Statman (1999) puts it shortly: people think *"some money is retirement money, some is fun money, some is college education money, and some is vacation money"* (p.19). Three key elements of Thaler's (1985) mental accounting theory are compounding principles, transaction utility and budgetary rules. Compounding principles refer to framing outcomes, aggregating or segregating them, in a way they increase their perceived utility. Transaction utility depends on the price the individual pays compared to a reference price: the total utility from a purchase is the sum of acquisition utility —the value of the good compared to the outlay— and transaction utility —which depends on the perceived merits of the deal. Finally, budgetary rules refer to the optimization process: individuals select the purchases that maximize the acquisition and transaction utilities of the goods purchased subject to a budget constraint.

Thaler (1999b) explains people engage in mental accounting activities in three instances. The first one captures how outcomes are perceived, and how decisions are made and then evaluated by assessing both ex ante and ex post cost-benefit results. The second one involves the assignment of activities to specific accounts —i.e., funds are *labeled*. Finally, the third one concerns the frequency with which accounts are evaluated. The three of them violate the economic principle of fungibility.[112] The model helps to explain some puzzles as why some markets fail to clear. Several other models feature mental accounting. The behavioral portfolio theory, BPT (Shefrin and Statman, 2000) introduces the possibility that investors segregate their portfolios within multiple mental accounts. Das et al. (2010) integrate some features of BPT and Markowitz's MPT into a mental accounting framework, and obtain a connection between investor consumption goals and portfolio construction. In addition, Barberis and Shleifer (2003) analyze the investors' tendency to categorize investments into groups, such as growth and value, and generate a number of empirical predictions.

An effect of mental accounting is that attitudes toward risk vary across mental accounts: people are often highly risk averse in some accounts and much less risk averse, even risk seeking, in others. Pan and Statman (2010) find empirical evidence of it. In addition, it may lead to a house money effect (Hens and Bachmann, 2008). Mental accounting and framing may be used to mitigate self-control problems (Thaler and Shefrin, 1981). Instead, loss aversion causes the decision making to be affected by the way alternatives are framed (Tversky and Kahneman, 1986). Following this, Barberis and Huang (2001) wonder what the relevant context for loss aversion is: gains and losses over total wealth, versus gains

[112] Two assets are fungible when, having the same characteristics, they are interchangeable. It implies money has no labels: the fungibility assumption is what permits all the components of wealth to be collapsed into a single number (Thaler, 1990).

and losses of each particular investment. They find the second approach —i.e., a *narrow framing* where investors are loss averse over the value of individual stocks— better to explain the observed behavior. Some ambiguities appear when consumption is temporally separated from purchase, such that the value of things can change due to depreciation, appreciation, personal taste, and others. Shafir and Thaler (2006) analyze these situations and identify some mental accounting rules people tend to use.[113]

Choice bracketing – Kahneman (2003a) says decision making is characterized by narrow framing and the related notions of mental accounting and decision bracketing —i.e., the grouping of individual choices into sets (Read et al., 1999). A set of choices are *bracketed together* when choices are made in a way they take into account the effect of each one on all other choices in the set, but not outside it.

4.2.3. Valuation / Errors of preference

The third group within the category of psychological biases consists of valuation and errors of preference. We divide this category in two groups. On one hand we include prospect theory (Kahneman and Tversky, 1979), a descriptive theory of choice that better explains how individuals evaluate the outcomes of risky prospects and choose in consequence. On the other hand, there is much empirical evidence as well that people make inconsistent choices when they make decisions over time. This group is related to the literature on intertemporal preferences that starts with the problems of self-control in intertemporal choice by Thaler and Shefrin (1981). Prospect theory, intertemporal preferences, and the biases that are related to them are summarized in Table 4.4. They are reviewed in detail below.

TABLE 4.4 – Valuation / Errors of preference

	VALUATION - ERRORS OF PREFERENCE		Related Concepts	Notes
Prospect Theory	REFERENCE POINTS	ANCHORING-AND-ADJUSTMENT	Conservatism Sunk costs fallacy	*After the 'Anchoring-and-adjustment dispute', it falls from the heuristics list to be considered among the 'errors of preference'. Anchoring closely related to reference points (Rabin, 1998)*
	LOSS AVERSION	Myopic loss aversion	Mental accounting	*Myopic loss aversion explains the equity risk premium and the disposition effect (Kahneman and Tversky, 1990)*
	DIMINISHING SENSITIVITY	Risk seeking	Favorite longshot bias	*Tversky and Kahneman (1992)*
Intertemporal preferences	PREFERENCE REVERSALS		Projection bias	*Projection bias: Loewenstein et al. (2003)*
		(Lack of) Self control	Precommitment	*Thaler and Shefin (1981): Mental accounting and framing to mitigate self control problems*
		Hyperbolic discounting		*Rabin (2002a)*
	Source dependence			Tversky and Kahneman (1992)
	Probability matching			Hens and Bachmann (2008)

Source: Own elaboration

Prospect theory is the most relevant descriptive theory of decision making under uncertainty. According to it, individuals evaluate the outcomes of risky prospects through a value function where the carriers of value are changes in wealth compared to a reference point rather than final assets, and a

[113] These include treating advances purchases (e.g., a case of wine) as investments, rather than spending, and then consider it for free or even as savings when it is eventually consumed as planned (a wine bottle opened for dinner). Costs are only associated with the event if it is not consumed as planned (the bottle is dropped and broken), with perceived costs being the cost of replacing the good, especially if replacement is likely.

probability weighting function where probabilities are replaced by decision weights. An extended version of prospect theory was later developed by Tversky and Kahneman (1992), called cumulative prospect theory, CPT. The theory accounts for a distinctive fourfold pattern of risk attitudes confirmed by experimental evidence: people tend to exhibit risk aversion for gains and risk seeking for losses of high probability, and risk seeking for gains and risk aversion for losses of low probability. In addition, the value function being steeper for losses than for gains implies loss aversion. These features stem from some particular characteristics of the value and weighting functions. Both functions are described next.

In prospect theory, people evaluate risks using transformed rather than objective probabilities, by applying a weighting function to the objective probabilities. This allows for the overweighting of tails, a modeling device that captures the common preference for a lottery-like, or positively skewed, wealth distribution (Barberis and Huang, 2008), in accordance with the empirical fact that people tend to put much weight on rare events. Thus, probability weighting may help explain the IPOs underpricing puzzle. Besides, individuals replace the utility function by a value function with three essential characteristics: reference dependence (the carriers of value are gains and losses defined relative to a reference point), loss aversion (the function is steeper in the negative than in the positive domain) and diminishing sensitivity (the marginal value of both gains and losses decreases with their size). This results in a value function that is concave above the reference point and convex below, kinked at the reference point, and represents investor's loss aversion. Moreover, diminishing sensitivity applies to the weighting function as well. These three essential features predicted under prospect theory, loss aversion, reference points, and diminishing sensitivity, are analyzed in what follows.

A. Reference points

In prospect theory, it is not final states what carries utility and matters for choice, but changes relative to a reference point. Just like one feels water at 20ºC fine when weather is cold, and cold when it is hot outside, perception is reference-dependent. A first study of reference points is in Helson (1964), who shows individuals tend to be more sensitive to changes with respect to some reference level rather than to absolute levels (Rabin 1998). Reference points are closely related to diminishing sensitivity and loss aversion, as well as to the status quo bias (Tversky and Kahneman, 1991), among others. Several candidates to be a natural reference point were suggested. In stock markets, Shefrin and Statman (1985) and Odean (1998a) suggest the privileged role by the buying price. Kõszegi and Rabin (2006) suggest the reference point is set by the subject's rational expectations given the economic environment. Kõszegi and Rabin (2007) describe different options —including the status quo, lagged status quo, and the mean of the chosen lottery— that generate inconsistent predictions on risk attitudes.[114] Then, using Kõszegi

[114] Under a status quo specification of the reference point, loss aversion predicts a high displeasure of modest-scale risks involving both gains and losses, and diminishing sensitivity predicts risk lovingness in high-probability losses. Under the lagged status quo (e.g., Thaler and Johnson, 1990) diminishing sensitivity predicts a willingness to take unfavorable risks to regain the previous status quo —i.e., disposition effect— inconsistent with the risk aversion predicted by a status quo model. Finally, under

and Rabin's (2006) model they suggest the predicted inconsistent risk attitudes may be manifestations of the same preferences in different domains.[115] Moreover, the model predicts less risk aversion when deciding whether to remove an expected risk than when deciding whether to take on that risk.

Another possibility is that the reference point varies from the purchase price to a new one as the stock price changes. Indeed, a relevant implication of prospect theory analyzed in a dynamic context is that reference points may change over time following gains and losses. Arkes et al. (2008) analyze this reference point adaptation, and discover an asymmetry: the magnitude of the adaptation is significantly greater following a gain than following a loss of equivalent size. The asymmetric adaptation suggests a mental accounting and hedonic maximization, as it results from the hedonic benefits of segregating intertemporal gains and integrating intertemporal losses (Thaler, 1999b). Baucells, Weber and Welfens (2011) study how reference points are updated after a sequence of information, and find they are not recursive, in the sense that the new reference point is not a combination of the previous one and the new information. Instead, they are a combination of the purchase (first) and the current (last) price of the time series. Finally, Arkes et al. (2010) analyze how cultural differences influence reference point adaptation (see *cultural differences*, subsection 4.3.2).

Anchoring-and-adjustment – Considered to be a key judgmental bias in risk perception, closely related to reference points (Rabin, 1998), anchoring-and-adjustment was initially seen as a heuristic but changed its classification after the enunciation of the attribution substitution. It is often referred to lead to underreaction (Barberis and Thaler, 2003) and to cause some relevant biases, such as conservatism (Shefrin, 2000). The literature starts with Tversky and Kahneman (1974), who set anchoring as one of the three basic heuristics in intuitive judgment. Early literature also includes Einhorn and Hogarth (1986), who develop a descriptive model of judgment under ambiguity where an initial estimate serves as an anchor and further adjustments are made for ambiguity. However, subsequent literature provided little or no support to this hypothesis. Then, Epley and Gilovich (2001) reestablished its validity by providing evidence that insufficient adjustment produces anchoring effects when anchors are self-generated. Epley and Gilovich (2006) provide experimental evidence. Finally, Oppenheimer et al. (2008) show anchors can operate across modalities. They show that for large or small anchors the notion of their general magnitudes may prime (that is, 'largeness' or 'smallness'), such that once a sense of size is activated individuals may exhibit bias in subsequent judgments. These results suggest the boundaries of anchoring effects may be wider than previously thought.

Finally, a closer insight on this bias is in a series of papers by Epley and Gilovich, compiled in Epley and Gilovich (2010). They see three waves of research on anchoring. The first wave starts with Tversky

---

specifications based on the certainty equivalent of the chosen lottery —e.g., the disappointment aversion model of Bell (1985) — loss aversion implies substantial aversion to any risk, which is inconsistent with the risk lovingness of the disposition effect.

[115] The model predicts both risk lovingness after surprise modest losses but risk aversion when a risk and the possibility to insure it are expected (matching both status quo prospect theory and disappointment aversion).

and Kahneman (1974), but they consider this wave over. The second one tries to set the psychological mechanisms that produce anchoring effects. These include a confirmatory hypothesis testing (Chapman and Johnson, 1994), numeric or magnitude priming (Oppenheimer, Leboeuf, and Brewer, 2008), and insufficient adjustment (Tversky and Kahneman, 1974; Epley and Gilovich, 2001). The third wave makes predictions about the consequences of anchoring. Epley and Gilovich suggest some lines of future research: analyzing the types of anchors that occur in everyday life, identifying social moderators of anchoring effects, and determining the sources of variability in the consequences of anchoring effects.

Conservatism – Defined as the slow updating of models in face of new evidence (Shleifer, 2000), conservatism explains why markets often respond gradually to new information (Chan, Jegadeesh and Lakonishok, 1996). It results in earnings reflecting bad news more quickly than good news (Basu, 1997). Thus, conservatism has been suggested to explain the profitability of momentum strategies (Chan et al., 1996) and the evidence of underreaction (Barberis et al., 1998). Early papers include Edwards (1968) —see Chapter 3— and analysis on multistage evaluation (e.g., Gettys, Kelly and Peterson, 1973).

Sunk costs fallacy – Prendergast and Stole (1996) define it as the unwillingness of individuals to respond to new information, and relate this bias to conservatism and cognitive dissonance reduction.

B. Loss aversion

As above mentioned, in prospect theory changes relative to a reference point determine utility. In addition, investors assign more significance to losses than to gains with respect to the reference point. This asymmetry in the value function is called loss aversion (Kahneman and Tversky, 1984): people suffer a loss more acutely than they enjoy a gain of the same magnitude (Shefrin, 2006). Loss aversion is thought to occur because people expect the pain of losing something to exceed the pleasure of gaining it, with the evidence of negativity biases in non-monetary domains reinforcing this belief (McGraw et al., 2010). However, that represents a contradiction to expected utility theory: Knetsch (1989) shows that if loss aversion is present, the basic property of EUT that two indifference curves never intersect no longer holds.[116] The influence of loss aversion in choices is observed in many contexts (Thaler, 1985; Kahneman, Knetsch and Thaler, 1990; Camerer, 2000; Novemsky and Kahneman, 2005) and may explain empirical findings like the disposition effect and higher levels of trade when prices are rising than when they are falling (Shefrin and Statman, 1985), how the number of market transactions may be reduced (Knetsch, 1989), why consumers and managers may take fewer risks (Rabin, 2000), and why stocks pay larger returns over bonds than theory predicts (Benartzi and Thaler, 1995). It is related to endowment effect and status quo bias (described in subsection 4.3.2). Loss salience (Hirshleifer, 2008) extends the notion of loss aversion to the social sphere: we care more about the financial losses than the financial gains of others. Finally, Tversky and Kahneman (1991) offer a theory of consumer choice where

[116] This requires indifference curves to be *reversible*: if a person owns *x* and is indifferent between keeping it and trading it for *y*, then if owning *y* it should be indifferent for him to trade it for *x*. (Kahneman et al., 1991).

losses have greater impact on preferences than gains, and provide empirical evidence that losses are weighted about twice as gains.

However, some limits of loss aversion were identified. Novemsky and Kahneman (2005) obtain experimental evidence that exchange goods given up as intended (e.g., money paid in purchases) do not exhibit loss aversion. It is individual's intentions —that is, defining a good as an object of exchange or of consumption— what codes outcomes as gains or losses, and determines whether giving up a good is evaluated as a loss or a foregone gain. McGraw et al. (2010) note empirical evidence of losses having greater effect on feelings than gains on judged feelings is mixed.[117] They suggest an interpretation: loss aversion requires people comparing gains and losses, but while choice enforces comparison, judging feelings does not necessarily require it —instead, we tend to consider similar outcomes for comparison (i.e., losses against losses).

Myopic loss aversion – A concept related to loss aversion is myopic loss aversion: the combination of loss aversion and the investors' common habit of evaluating their portfolios frequently (Benartzi and Thaler, 1995). It rests on two behavioral principles: loss aversion and mental accounting. It helps to explain the equity risk premium, the disposition effect, and implies that the decision making is affected by the way alternatives are framed. Finally, Thaler et al. (1997) find experimental evidence of two implications: investors will be more willing to accept risks if they evaluate their investments less often, and if all payoffs are incremented enough to eliminate losses, investors will accept more risk.

C. Diminishing sensitivity

The third essential feature of prospect theory applies to both the value and weighting function. Diminishing sensitivity states that the impact of a change diminishes with the distance to the reference point (Tversky and Kahneman, 1992). Then, marginal effects in perceived well-being are greater for changes close to the reference level than for changes further away (Rabin 1998). Kahneman and Tversky (1979) note that diminishing sensitivity is a pervasive pattern of human perception, being perceptions a concave function of the magnitudes of change. Hence, they conjecture the value function would be concave for gains and convex for losses, reflecting the principle of diminishing sensitivity. This implies different attitudes toward risk: while people are likely to be risk averse over gains, they are often risk-loving in the domain of losses (i.e., we are willing to gamble to avoid losses). Diminishing sensitivity applies to the weighting function, too (Tversky and Kahneman, 1992): *"In the evaluation of uncertainty, there are two natural boundaries —certainty and impossibility— that correspond to the endpoints of the certainty scale. Diminishing sensitivity entails that the impact of a given change in probability diminishes with its distance from the boundary"* (p. 303). Two related biases follow next.

[117] For example, Mellers et al.'s (1997) study emotional reactions *"to outcomes of mixed gambles (e.g., win or lose $16) on a standard bipolar scale from -50 (extremely disappointed) to +50 (extremely elated), and found that gains and losses were rated as roughly equal in intensity. Other studies have provided only limited evidence of an asymmetry"* (McGraw et al., 2010, p. 3).

Risk seeking – Prospect theory asserts most people are risk averse, as standard finance predicts, but only when confronted with the expectation of a financial gain. Instead, when facing the possibility of losing money, people often behave as a risk lover, preferring to gamble if there exists a possibility to avoid a sure loss. Thus, this feature is also known as aversion to a sure loss: people choose to accept an actuarially unfair risk in an attempt to avoid a sure loss (Shefrin, 2006). More specifically, risk-seeking choices are common to be observed in two types of choices, namely aversion to a sure loss and the favorite-longshot bias (Tversky and Kahneman, 1992). The first type stems directly from the shape of the value function; the favorite-longshot bias, instead, represents a miscalibration of probabilities that is often related to the probability weighting function —see next.

Favorite-longshot bias – It is often observed in betting markets that bettors tend to put too much weight on rare events (longshot bets) while they underestimate the probability of favorites. Thus, the expected return on longshot bets tends to be systematically lower than on favorite bets (Ottaviani and Sorensen, 2007), or alternatively, the normalized prices on the favorites understate their winning chances while the normalized prices on the longshots exaggerate their winning chances (Shin, 1992). A common manifestation of a risk-seeking behavior, the favorite-longshot bias is one of the most studied biases in behavioral finance and other disciplines. The first documentation is attributed to Griffith's (1949) observation of this behavior in horse-race betting. Classic papers include Shin (1992) and Woodland and Woodland (1994). Recent studies include Hodges, Tompkins and Ziemba (2008), who observe a favorite-longshot bias in the derivatives markets,[118] and Ottaviani and Sorensen (2007), who review the main theoretical explanations suggested, including a misestimation of probabilities (Griffith, 1949), market power of informed bettors, preference for risk, heterogeneous beliefs, market power by uninformed bookmakers (Shin, 1992), limited arbitrage by informed bettors, and simultaneous betting by partially informed insiders (Ottaviani and Sorensen, 2007).

D. Preference reversals

When people make decisions over time, their intertemporal preferences are rational if they are time consistent —i.e., if they exhibit no preference reversals as time passes (Hens and Bachmann, 2008). However, empirical evidence shows people do exhibit preference reversals, have problems to commit with decisions they had taken in the past, and exhibit present-biased preferences. For simplicity, we see these concepts together under the epigraph of preference reversals.

Economists compare preferences over time with exponential discounting, what implies time consistency. However, psychological research shows this assumption is wrong: preferences vary over time. The first to notice were perhaps Phelps and Pollak (1968), who reviewed Ramsey's postulate that

[118] They find investors tend to pay too much for deep out-of-the-money call options (longshots) because they are seen as a sort of lottery tickets.

all generations exhibit a *perfect altruism*.[119] More recently, Kirby and Herrnstein (1995) show changes in delayed rewards make subjects' preferences reverse from a larger, later reward to a smaller, earlier reward as the delay decrease. Related to preference reversals is the existence of a *projection bias*: people exaggerate the degree to which their future tastes will be similar to their current ones. Loewenstein, O'Donoghue and Rabin (2003) provide evidence and model this bias, which presumably stems from habit formation, and which makes people consume too much early in life, and to consume more and save less than originally planned as time passes. Finally, two important consequences of preference reversals are that people exhibit problems of self-control and a present bias. We see both concepts in what follows.

Self-control (and precommitment) – We sometimes make certain decisions precisely to restrict our own future flexibility (Rabin, 1998). Strotz (1955) realized that a person, when choosing a plan of consumption for the future, might recognize he later might not obey to that plan. Knowing this, he may choose to *precommit* his future behavior by excluding future options, or by modifying his plan as to take account for future disobedience. Those who are aware of their future self-control problems would be sophisticated, and those who are not, naive. Loewenstein (1996) concludes, however, that any of us may end up being naive indirectly due to psychological biases that makes us mispredict changes in utility. Thaler and Shefrin (1981) suggest mental accounting and framing may be used to mitigate self-control problems. Finally, Shefrin (2000) relates self-control to preference for dividends: some investors may prefer dividends because they don't want to dip into capital.

Hyperbolic discounting – Also known as present bias. Standard economic models assume people discount streams of utility over time exponentially. However, this has been shown to generate time-inconsistent preferences, with ample evidence that people exhibit present-biased preferences instead (Rabin, 2002a): *"We are more averse to delaying today's gratification until tomorrow than we are averse to delaying the same gratification from 90 days to 91 days from now. This difference in attitudes towards delay in gratification generates time inconsistency when considering potential dynamics of behavior"* (p. 668). A way to account for present-biased preferences is to apply hyperbolic discounting. Thus, standard economics model exponential discounting as

$$U^{\tau} = \int_{t=\tau} e^{-r(t-\tau)} \cdot u_t \tag{4.1}$$

where U^{τ} are intertemporal preferences, u_t instantaneous utilities, and $r>0$ a parameter. Continuous-time hyperbolic discounting would be instead expressed as

$$U^{\tau} = \int_{t=\tau} \frac{1}{(t-\tau)+k} \cdot u_t \tag{4.2}$$

[119] Phelps and Pollak (1968) describe Ramsey's postulate: *"each generation's preference for their own consumption relative to the next generation's consumption is no different from their preference for any future generation's consumption relative to the succeeding generation"* (p. 185). However, what if people do not subscribe to this ethic? Phelps and Pollak investigate the optimal saving policy of an imperfectly altruistic present generation, an antecedent to the study of changes in preferences.

where *k>0* is a parameter. Alternatively, since the continuous-time hyperbolic discounting function is difficult to deal with and its specific functional form not very important, we can model present-biased preferences with a discrete-time discounting function of the type

$$\text{for all t, } U^t\left(u_t, u_{t+1}, \cdots, u_T\right) \equiv \left(\delta\right)^t u_t + \beta \sum_{\tau=t+1}^{T} \left(\delta\right)^{\tau} u_{\tau} \tag{4.3}$$

where parameters β and δ are less than 1, with δ very close to 1. The discrete-time exponential model corresponds to β = 1. While exponential discounting is a theory of 100% short-term patience, present-biased preferences account for different immediate and future discounting: one can be extremely patient in the long run and very impatient in the short run. Camerer and Loewenstein (2004) highlight this *immediacy effect* as the most striking consequence of time discounting: *"discounting is dramatic when one delays consumption that would otherwise be immediate"* (p. 23).

E. Other errors of preference

Source dependence – People's willingness to bet on an uncertain event depends not only on the degree of uncertainty but also on its source (Tversky and Kahneman, 1992).

Probability matching – Another violation of rationality on binary choice problems is a tendency to *match* probabilities, allocating responses in proportion to their relative payoff probabilities (Hens and Bachmann, 2008). For instance, people often choose 49% heads and 51% tails when they know an unfair coin has those probabilities, when the optimal choice would be, indeed, to always select tails.

4.2.4. Social factors

The last group of psychological biases consists of social factors: cultural and social influences on individual's behavior. The main biases in this group are summarized in Table 4.5 and reviewed below.

TABLE 4.5 – Social factors

SOCIAL FACTORS		Related Concepts	Notes
SOCIAL CONTAGION	Obediency to authority	Herd behavior	*Social contagion: Asch's (1952) experiment. Shiller (2000b) links herding to social contagion and obedience to authority*
	Communal reinforcement		*Shiller (1984)*
	Groupthink theory	(Collective) Confirmatory bias	*Lunenburg (2010)*
	Persuasion		*Johnson and Eagly (1989)*
STATUS, ENVY, SOCIAL COMPARISON		Self esteem, Pride, Prejudice	Rabin (1998)
		Cooperation, altruism	
INFORMATIONAL CASCADES	Availability cascades	Asset bubbles	*Shiller (2002b) cites cascades as one of the causes of the dot-com bubble*
		Herding	*Bikhchandani et al (1998) relate informational cascades and herding*
GLOBAL CULTURE	Cultural differences		*Guiso et al. (2006); Statman and Weng (2010)*
GREED AND FEAR		Familiarity	*People exhibit fear of the unknown, causing familiarity (Cao et al., 2011)*
		Status quo bias	*Fear of change causes a status quo bias (Samuelson & Zeckhauser, 1988)*
FAIRNESS, RECIPROCITY & JUSTICE	Trust		Kahneman et al. (1986a)

Source: Own elaboration

A. Social contagion

Social contagion was first reported in the classic Asch's experiment (Asch, 1952): a subject was placed into a group of several people confederated with Asch, and asked to answer a sequence of questions about the lengths of some line segments shown to them. The subject heard other people's answers before giving his own answer. Every time the confederates gave unanimous and obviously wrong answers, most subjects tend to answer the same. Moreover, they often showed signs of anxiety or distress that evidence they surrendered to avoid being seen as different of foolish before the group.

Ach's experiment highlights the power of social pressure on individual judgment. Shiller (1984) claims then that a consequence of social dynamics on markets is that fads influence financial markets just as they do in instances such as fashion or politics.[120] Manski (2000) surveys the literature on social interaction and suggests the neoclassical view, where non-market interactions are not of interest, ends by the 1970s when some developments in micro, macro and labor economics expose the importance of the economic analysis of social interactions —in particular, the adoption of non-cooperative dynamic game theory. Finally, a basic distinction between social interaction literature and literature about culture, which we will review later in this section, is that the former focuses on peer group effects that can be viewed as the fast-moving component of culture (Guiso, Sapienza and Zingales, 2006), while culture-related topics rely on inherited, slow-moving components of culture.

Obedience to authority – Milgram's experiments (Milgram, 1963, 1974) show few people has the initiative to resist authority, to the point of performing acts that violate their deepest moral beliefs: most subjects were willing to hurt or even kill another person if they were simply asked to do it, with no coercive methods, by a person or an institution they recognized as an authority. A few years before, Festinger (1957) analyzed the effects of forced compliance, showing that a person forced to do something contrary to her opinion may eventually change her view in order to avoid cognitive dissonance. Shiller (2000b) links herd behavior to social contagion and obedience to authority: Asch's experiment evidence the immense power of social pressure on individual judgment; Milgram's experiments, the enormous power of authority over the human mind. Thus, Shiller suggests, the study of asset bubbles could draw upon epidemic models used by sociologists to predict the course of word-of-mouth transmission of ideas.

Communal reinforcement – Communal reinforcement is a type of social dynamics. Early articles on social psychology of individual suggestibility, group pressure and diffusion of opinions include Katona (1901), Sherif (1937) and Asch (1952). Katona uses the term social learning for the process of *"mutual reinforcement through exchange of information among peer groups by word of mouth, a major condition for the emergence of a uniform response to new stimuli by very many people" (p.203)*. Sherif

[120] Investors follow gurus, read magazines, discuss investments with other investors, gossip about others' successes or failures... and through this process, market psychology influences markets (Shiller, 1984).

shows how individual opinions are influenced by the opinion of others in his classic experiment on the *autokinetic effect*.[121] Asch, as we have seen, finds evidence of decision errors under social pressure.

Groupthink theory – Groupthink, a term coined by Janis (1972), is the tendency of cohesive groups to reach consensus without offering, seeking or considering alternative hypothesis (Lunenburg, 2010). Janis identifies some symptoms of groupthink, including an illusion of invulnerability which lead groups to take excessive risks, or members imposing themselves a self-censorship to avoid appearing as a dissenter. Shefrin and Cervellati (2011) interpret it as a form of collective confirmation bias.

Persuasion – Under some circumstances, people may be persuaded by others to think or act in a specific way. A classic concept to explain when persuasion succeeds is *involvement* (Johnson and Eagly, 1989): the closer the values and attitudes by the persuader and how the individual defines himself, the stronger the involvement. Persuasion has been widely studied in areas such as marketing, politics, and sociology. Examples are Di Blasio and Milani (2008), who show persuasion succeeds better in face-to-face conditions; DellaVigna and Kaplan (2007), who show the ability of media to persuade voters; and Todd and Miller (1999), who analyze the effects of persuasion in mate search.

B. Status, envy and social comparison

An important field of social psychology relevant to economics refers to self-perception compared to others, and the feelings of jealousy, self-esteem, pride or prejudice such comparison provokes. We denote this category 'status, envy and social comparisons' as in Rabin (1998). Not all feelings stemming from social comparisons are negative, as cooperation (Argyle, 1991) or reciprocal altruism (Trivers, 1971) fall within this category. Examples of this literature are Salovey and Rodin (1984) on jealousy; Gilbert, Price and Allan (1995), who suggest social comparison occurs in many forms of human interaction, such as relative social hierarchy (status), sexual selection, competition for parental investment, or reciprocal exchange and altruism; and Richins (1991), who reviews the literature on consumer dissatisfaction when they compare themselves with the idealized advertising images.

C. Informational Cascades

News media often act as precipitators of attention cascades: significant market events only occur if large groups of people think the same, and news media could be the vehicles for such spread of ideas. Shiller (2000b) cites informational cascades among the causes of the dot-com bubble. Bikhchandani, Hirshleifer and Welch (1998) argue that some puzzling phenomena such as herding, fads, asset bubbles and crashes may be seen as consequences of informational cascades. We learn by observing what others do, and then imitate those acts. Such propensity to imitate would be an evolutionary adaptation for survival, allowing individuals to take advantage of the hard-won information of others.

[121] Subjects seated in a totally darkened room were asked to report the magnitude of the movement of a point of light five meters ahead. They reached consensus on the magnitude when, in fact, the point of light wasn't moving at all (Shiller, 1984).

Availability cascades – Related to informational cascades, these are self-reinforcing processes of collective belief formation that have a combination of informational and reputational motives as driving factors (Kuran and Sunstein, 1999). By the availability heuristic, people judge the importance of a theme according to their ability to remember examples of it. Then, as a chain reaction result, the more people talk about an issue —and media often play a relevant role here— the more relevant it seems due to its rising availability in public discourse, leading to a self-reinforcing cycle (Hirshleifer, 2008).

D. Global culture

Culture refers to the values that ethnic, religious, and social groups transmit across generations (Guiso et al., 2006; Statman and Weng, 2010). The first to note culture is a determinant of economic growth was perhaps Weber (1905), who argued the Protestant Reformation was crucial to the development of capitalism. Economists have been reluctant to use culture as an explanatory factor, perhaps because of the vague and ubiquitous ways culture can enter the economic discourse, making it difficult to design testable hypotheses (Guiso et al., 2006). Nonetheless, recent techniques and data available have made it possible to identify systematic differences in people's beliefs, and relate them to their cultural legacy. Thus, the way people perceive events is influenced by culture (Levinson and Peng, 2007). Nisbett and Masuda (2003) describe how East Asians and Westerners perceive the world and think of it differently.[122] Cultural psychology has a significant influence on social psychology as well (e.g. Miller, 1984). Shiller (2000a) notices the emergence of a global culture in examples of imitation or convergence of fashions across countries separated by physical and language barriers. Shiller (2000b) suggests cultural factors help explain the dot-com bubble, such as the belief we were in a new era.

Cultural differences – Though a global culture might be emerging, cultural differences are still ubiquitous. Empirical evidence includes Arkes et al. (2010), who study cultural differences between China, Korea and the U.S., in reference point adaptation following gains or losses in security trading. Differences between Asians and Americans are also studied by Ji et al. (2001), who show Chinese, compared to Americans, anticipate more changes and are more likely to predict the direction of change; Levinson and Peng (2007), who find significant differences in how framing, morality and out-group information affects judgments of American and Chinese cultures; and Chen et al. (2007), who find differences among Chinese and American investors regarding overconfidence and disposition effect. Some authors analyze how culture impacts on expectations and preferences. These include Guiso et al. (2006), on the role culture plays to determine prior beliefs in decision making, Henrich et al. (2001), on variations across tribes in their responses to the classic ultimatum and dictator games,[123] and Hoff and

[122] East Asians exhibit a broader perceptual and conceptual view of the world, noticing relationships and changes. They tend to group objects based on family resemblance and live in complex social networks. Westerners, instead, live in less constraining social worlds and attend more to single objects and their goals with respect to them.
[123] A 2-person ultimatum bargaining game is a perfect information game where on every stage of the bargaining process only one player has the option to offer a proposal which the other party can either accept or reject. A dictator game would be similar, but where the second player has to accept what is being offered.

Priyanka (2004), who show the effects of social inequality linger: beliefs that are the legacy of extreme inequality conditions for generations determine individual's expectations that reproduce the inequality. Finally, other authors have focused instead on cultural differences in economic and financial variables. Examples are Statman and Weng (2010), who find immigrants exhibit different borrowing patterns and real estate and international investing long after they settled in their new countries, and Stulz and Williamson (2003), who claim culture may affect finance through three channels: the country values, its institutions, and how resources are allocated.

E. Greed and Fear

Shefrin's "Beyond Greed and Fear" (Shefrin, 2000) identifies human emotions as the determinants of risk tolerance and portfolio choice, with fear and greed being the main drivers. However, Shleifer (2004) claims that the unethical conduct usually blamed to stem from greed is often a consequence of market competition.[124] Fear, greed, and other emotional responses have been argued against the efficient market hypothesis. Thus, Lo, Repin and Steenbarger (2005) offer experimental evidence that even the most experienced traders exhibit strong emotional responses to increases in price volatility and that there is a negative correlation between successful trading behavior and emotional reactivity. Pan and Statman (2010) show risk tolerance varies with conditions and the emotions associated to them. Thus, tests of risk tolerance performed after periods of high stock returns are likely to exaggerate investors' risk tolerance. In addition, fear is often related to other biases: fear of the unknown would be an explanation for the familiarity heuristic (Cao et al., 2011); fear of change, a possible explanation for the status quo bias (Samuelson and Zeckhauser, 1988); while fear and greed play a key role in concepts like market sentiment, bubbles and crashes, social contagion, and others (Shiller, 2000a; Shefrin, 2000).

F. Fairness, Reciprocity and Justice

According to Kahneman, Knetsch and Thaler (1986b), *"the absence of considerations of fairness and loyalty from standard economic theory is one of the most striking contrasts between this body of theory and other social sciences"* (p. S285). Camerer and Loewenstein (2004) observe people spend money to punish others who have harmed them, to reward those who have helped, or to make outcomes fairer. Güth, Schmittberger and Schwarze (1982) conduct a series of dictator and ultimatum games to show people often rely on what they consider to be a fair or justified result.[125] This shows most individuals prefer an inefficient result rather than an unfair result, even if it goes against their interests (Stiglitz, 2012). Further analyses of these games are available in Camerer and Thaler (1995) —about ultimatum games— and List (2007) —about dictator games.

---

[124] Shleifer shows the role of competition, as opposed to greed, in the spread of five censured activities: employment of children, corruption, excessive executive pay, corporate earnings manipulation, and involvement of universities in commercial activities.
[125] In dictator games, rather than taking everything for themselves (the normative solution), subjects often offer something to the counterpart. In ultimatum games, rather than sharing only the smallest possible positive payoff, offers are usually within 30 to 40 percent of the given amount, while their counterparts tend to reject the proposal when it offers less than 20 percent.

For behaviorists, it is a short-sighted view to believe firms simply maximize profits subject only to legal and budgetary constraints: markets that fail to clear evidence that some additional constraints are operative (Kahneman et al., 1986a,b). Akerlof (1979) and Solow (1980) use fairness to explain why firms often do not cut wages during periods of high unemployment, giving rise to the literature of efficiency wages where higher wages increase productivity (Akerlof and Yellen, 1990; Fehr and Falk, 1999). Okun (1981) says fairness can also alter the outcomes in customer markets —where suppliers have some monopoly power and repeat business with their clientele. Thaler (1985) and Kahneman et al. (1986a,b) find fairness is relevant for customers to determine their reference prices, with loss aversion playing a key role in what they find to be acceptable. Stiglitz (2012) goes further: the perception of an increasing inequality and that our economic system is unfair may have very harmful effects over our democracies. Additional literature includes Bolton and Ockenfels (2000) on equity and competition; Falk, Fehr and Fischbacher (2003) on fairness; and Sen (1995) on moral values.

Fairness and justice are related to other concepts, like money illusion: people observe nominal rather than real changes in wages and prices to assess the fairness of a firm's behavior (Kahneman et al, 1986a). The endowment effect implies people feel foregone gains (opportunity costs) less painful than perceived losses (*out-of-pocket* costs). Hence, our perceptions strongly depend on whether a question is framed as a gain reduction or an actual loss (Kahneman et al., 1991). Finally, Shleifer (2004) analyzes the relationship between ethics and efficiency. When ethical norms promote cooperative behavior they help for the successful functioning of social institutions and so, ethics and efficiency go together. Three ways to avoid unethical behavior are long-run market pressure, moral suasion and regulation. Shleifer suggests they are limited and advocates for competition:[126] it would lead to economic growth and wealth creation, and as societies grow richer their ethics will change to emphasize cooperation and inclusion.

Trust – Pan and Statman (2010) identify trust as one of the five deficiencies of risk tests aimed to help investors' advisors. Trust matters to advisors since trusting investors are likely easier to guide.

4.3. BEHAVIORAL CONSEQUENCES

Our taxonomy separates psychological biases and the consequences of those biases. These behavioral consequences, known as anomalies, are empirical results that are difficult to rationalize. Following Barberis and Thaler (2003), we split this category into market anomalies and investor behavior anomalies —what we call decision effects. We analyze them separately in what follows.

[126] People express concern for child labor, but they want cheaper shoes; moral suasion works when competition is less keen, but not when companies are bounded by the imperative of commercial survival; and government regulation is limited to battle against cost-reducing competition —that is why corruption, child labor and bad accounting practices remain so pervasive.

4.3.1. Market anomalies

A classic field in finance is the literature on financial market anomalies. We reviewed them in Chapter 2, so in most instances we will refer to that chapter for further description. Another field are the anomalies in the decisions companies make. Thus, we divide this category in financial markets anomalies and anomalies in corporate finance. The most relevant are summarized in Table 4.6 and reviewed below.

TABLE 4.6 – Market anomalies

MARKET ANOMALIES	Related Effects and Trading Strategies	CAUSAL FACTORS	Notes
FINANCIAL MARKET ANOMALIES			
EXCESS VOLATILITY	Sentiment, cascades and bubbles	Heuristics Prospect theory and Mental accounting	*Shiller (1979, 1981)* *Related to sentiment, cascades... (Raghubir & Ranjan Das, 1999)* *Prospect theory and mental accounting explain the excess volatility (Barberis et al. 2001).*
EXCESSIVE TRADING VOLUME	Gambling and speculation	Attention anomalies, Disposition effect Overconfidence, illusion of control	*Attention anomalies and disposition effect (Odean, 1999)* *Overconfidence (Odean, 1998b);* *Illusion of control (Raghubir & Ranjan Das, 1999)*
OVERREACTION	Long term reversals CONTRARIAN INVESTING	Beliefs (representativeness, overconfidence) Preferences (loss aversion, narrow framing) Gambler's & hot hand fallacies	*Overreaction & long term reversals: De Bondt & Thaler (1985)* *Beliefs and preferences: Barberis and Thaler (2003)* *Gambler's and hot hand fallacies explain both over and underreaction (Rabin 2002b)*
UNDERREACTION	MOMENTUM POSITIVE FEEDBACK TRADING	Anchoring, Conservatism Overconfidence, Disposition effect	*Momentum: Jegadeesh & Titman (1993)* *Conservatism (Chan et al., 1996)* *Beliefs and preferences: Barberis and Thaler (2003)* *Disposition effect (Grinblatt and Han, 2005)*
HERDING		Social contagion	*Herding would be related to social contagion (Shiller, 2000a)*
RETURN PREDICTAB. (time series)	Dividend-to-price ratio		*Fama & French (1988)*
RETURN PREDICTAB. (cross-sect)	Scale-Price ratios Event studies	Heuristics, Prospect th., Mental accounting	*IPO-related pricing anomalies caused by prospect theory and mental accounting (Barberis & Huang, 2008)*
EQUITY PREMIUM PUZZLE	Stock market participation puzzle	Myopic loss aversion (loss aversion & framing) Ambiguity aversion	*Mehra and Prescott (1985)* *Myopic loss aversion explains the puzzle: Benartzi & Thaler (1995)* *Ambiguity aversion: Maenhout (2004)*
FORWARD PREMIUM PUZZLE		Overconfidence	*Burnside et al. (2011)*
CLOSED-END FUND PUZZLE		Mental accounting	*Related to mental accounting (Raghubir & Ranjan Das, 1999)*
ANOMALIES IN CORPORATE FINANCE			
DIVIDEND PUZZLE		Self-control, Prospect theory	*Shefrin and Statman (1984)*
BUSINESS FAILURE		Overconfidence	*Camerer and Lovallo (1999)*
HIGH RATES OF M&A		Overconfidence	*Roll (1986), Malmendier and Tate (2008)*
CORPORATE DIVERSIFICATION		Overconfidence	*Malmendier and Tate (2008)*

Source: Own elaboration

A. Excess volatility

As described in Chapter 2, Shiller (1979, 1981) impose a theoretical limit on bond and stock market volatility, respectively. Using the dividend discount model (DDM), Shiller demonstrates that, though the efficient markets model does not say stock prices p should be equal at any time to their ex post rational counterpart p^* (given by DDM), two theoretical volatility bounds must hold:[127]

[127] The first inequality comes from the fact that, if markets are efficient, then $p^* = p + \varepsilon$, where ε is a white noise prediction error, that is uncorrelated with p. Hence, the variance of the stock price series, p, must be lower than the variance of the ex post counterpart, p^*, given by DDM. The second inequality starts from the concept of 'innovation in a variable', $\delta_t = E_t - E_{t-1}$. The expected innovation in stock prices, when prices are derived from expected future dividends (as in DDM), is equal to $\delta_t \cdot p_t = \Delta p_t + d_{t-1} - r \cdot p_{t-1}$. Since innovations are serially uncorrelated, and assuming price (and dividend) stationarity, Shiller ends up with an optimization program for var(δp), that is, he looks for the highest possible variance of stock price innovations that could be explained by innovations in dividends. The solution for that optimization program is equation (4.5).

$$\sigma(p) \leq \sigma(p^*) , \tag{4.4}$$

$$\sigma(\Delta p) \leq \frac{\sigma(d)}{\sqrt{2r}} , \tag{4.5}$$

where d is the dividend paid and r the real interest rate (cost of capital). Likewise, Shiller (1979) shows that an upper limit on the volatility of the long-rate series exists. An equation similar to (4.4) applies to interest rate markets, with the holding period return, H, on bonds playing the role of Δp, and the short term interest rate, r, playing the role of dividends. That is:

$$\sigma(H) \leq \frac{\sigma(r)}{\sqrt{2r}} . \tag{4.6}$$

These bounds show that the fundamental principle of optimal forecasting is that the forecast must be less variable than the variable forecasted. However, Shiller (1979, 1981) provides empirical evidence that those limits were *dramatically violated* in stock markets —as well as in bond markets, though to a lesser extent. Since empirical evidence shows most market volatility is not explained by fundamentals, this puts into question the entire efficient markets theory (Shiller, 2003).

Some authors suggest Shiller's work misspecifies some fundamental values and has econometric difficulties. Following Merton (1987), Shiller (1981) makes three assumptions: prices reflect rational expectations of future dividends, the real expected rate of return is constant over time, and aggregate real dividends can be described by a finite-variance stationary stochastic process with a deterministic exponential growth rate. Merton asserts there is evidence to reject the second one, but Grossman and Shiller (1981) obtain similar results with a discount factor equal to the intertemporal marginal rate of substitution for consumption —as described in Chapter 2. In addition, Kleidon (1986) reports evidence against stationarity for both stock prices and dividends. Later work would correct the stationary assumption: Campbell and Shiller (1988a) model dividends and stock prices in a more general way, and get results that support the excess volatility. Similar results were obtained by West (1988a,b), Campbell and Shiller (1988b), Campbell (1991) and LeRoy and Parke (1992). Barsky and DeLong (1993), instead, show that if dividend growth rates are unstationary, EMM looks closer to the data.

B. Excessive trading volume

Odean (1999) suggests trading volume in financial markets seems higher than rationally expected for rebalancing and hedging needs, and provides evidence that it is indeed excessive for investors with discount brokerage accounts. Shefrin and Statman (1994) and Odean (1998b) suggest overconfidence would cause the excessive trading. Odean (1999) tests the hypothesis, but the results are too extreme to be explained only by overconfidence. Additional causes would be the disposition effect, attention anomalies, reluctance to sell short, gambling and speculation, and illusion of control.

Gambling and speculation – Shiller (2000a) reports that about 4% of men and 1,5% of women were probably or potentially addicted gamblers in the U.S. by 1974, and suggests compulsive gambling is only an extreme form of a more common behavior. This tendency to gamble has always represented a puzzle in the study of behavior under uncertainty, since it shows people simultaneously exhibit risk aversion (insurance) and a risk-loving behavior (gambling). This propensity to gamble would be a partial explanation for excessive trading, bubbles in speculative markets, and irrational exuberance.

C. Overreaction and underreaction

As we saw in Chapter 3, De Bondt and Thaler (1985) use Kahneman and Tversky's (1982a) insights to show markets overreact. Then, Jegadeesh and Titman (1993) show they may underreact as well.[128] A full reconciliation of both theories, under the behaviorist paradigm, would come with models by Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999) and Lee and Swaminathan (2000), among others. All these models assume investors' cognitive and emotional biases to explain both under and overreaction. Barberis and Thaler (2003) summarize three groups: beliefs (conservatism, representativeness, overconfidence...), institutional frictions, and preferences (loss aversion, narrow framing). Thus, a market overreaction that eventually reverses (a.k.a. *long term reversal* or *mean reversion*) makes a *contrary investing* strategy profitable, while a market that underreacts is a good place for investors to perform *momentum* and *positive feedback trading* strategies. Finally, other investors simply might try to follow what others do, a strategy known as *herding*. In what follows we review contrary investing, momentum and positive feedback trading, and leave herd behavior for a subsequent section.

Contrarian investing – A negative autocorrelation in stock returns (Fama and French, 1988b) suggest the profitability of contrary investing strategies over long horizons (De Bondt and Thaler, 1985). However, later research would find little or no evidence of mean reversion, including Jegadeesh (1991), Kim, Nelson and Startz (1991), McQueen (1992), and Gangopadhyay (1996). The validity of previous research suggesting empirical evidence of mean reversion was also put under question by Lamoureux and Zhou (1996), who criticize the properties of the tests used to detect predictability in stock prices. Gropp (2004) came to address these critiques, providing a rationale for the failure of previous research to detect mean reversion: the standard methods classify stocks by market capitalization, what fails to account for temporary shocks in prices and decreases the likelihood of detecting mean reversion. To

[128] Evidence of overreaction includes Fama and French (1988b), Poterba and Summers (1988), and Cutler, Poterba and Summers (1991) of slight negative autocorrelation in stock returns over horizons of three to five years; Campbell and Shiller (1988a), Kothari and Shanken (1997) and Pontiff and Schall (1998) that low dividend yields and book to market ratios predict a low subsequent return; Campbell and Kyle (1993) that stock prices respond more to news about fundamentals than it otherwise would do. Evidence from the cross-section of stock returns by De Bondt and Thaler (1985), Chopra, Lakonishok and Ritter (1992), of earnings by Zarowin (1989), of price to book value by De Bondt and Thaler (1987), Fama and French (1992), and of price to cash flow by Lakonishok, Shleifer and Vishny (1994). Evidence of underreaction include Cutler et al. (1991) for aggregate time series of security returns; Bernard (1992), Jegadeesh and Titman (1993) or Chan et al. (1996) for cross-section of stock returns; again Chan et al. (1996) and Rouwenhorst (1998) of underreaction to earnings announcements; Ikenberry, Lakonishok and Vermaelen (1995) to share repurchases; Ikenberry, Rankine and Stice (1996) to stock splits; Michaely, Thaler and Womack (1995) to dividend initiations; Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) to SEOs.

solve it, he uses industry-sorted portfolios instead, and finds strong evidence of mean reversion in industry portfolios for the U.S. over the period 1926–1998 which, after temporary shocks, revert halfway toward their fundamental levels over 4–8 years.

Momentum – The profitability of momentum strategies (Jegadeesh and Titman, 1993) seems to be consistent. Chan et al. (1996) note the sources of profitability may come from past returns or recent earnings surprises. In addition, momentum does not appear to be only driven by positive feedback trading (because drifts in returns are not subsequently reversed).[129] In consequence, rationalists like Fama and French (2012) seem to have subscribed to this evidence, but they consider it may be explained by economic risk factors that affect investment life cycles and growth rates (Chordia and Shivakumar, 2002), like interest rates and slow turnover in the firm's project portfolio, what leads to persistence in systematic risk (Berk, Green and Naik, 1999). However, Griffin, Harris and Topaloglu (2003) review recent empirical research —including Jegadeesh and Titman (1993), Fama and French (1996) and Grundy and Martin (2001)— and claim it favors the behaviorist interpretation that momentum is not driven by market risk. Moreover, Jegadeesh and Titman (2001) show momentum returns quickly dissipate after the investment period, rejecting the rationalist hypothesis.[130] Behavioral interpretations include conservatism (Chan et al. 1996), imperfect formation and revision of investor expectations in face of new information (Barberis et al., 1998; Daniel et al., 1998), a neglected firms' effect due to low analyst coverage (Hong, Kubik and Solomon, 2000), and the disposition effect (Grinblatt and Han, 2005).

Positive feedback trading – A trading strategy often related to momentum (e.g., Grinblatt, Titman and Wermers, 1995) and herding, trend chasing or positive-feedback trading was first described in DeLong et al. (1990b), who test whether it might induce the profitability of momentum strategies, and find trend chasers reinforce stock prices movements even in the absence of fundamental information. Nonetheless, Chan et al. (1996) suggest momentum is not entirely driven by positive feedback trading, as drifts in future returns are not subsequently reversed. Lakonishok, Shleifer and Vishny (1992) find evidence of positive-feedback trading among institutional traders for smaller stocks, but relatively little evidence in blue chips. Nofsinger and Sias (1999), on the contrary, find that institutional investors use positive feedback trading more often than individual investors.

D. Herd behavior ('herding')

Herding is a mutual imitation (Welch, 2000), the tendency of managers to *follow the herd* —that is, to mimic the investment decisions of other managers. Hwang and Salmon (2004) define it as imitation and suppression of private information. Early literature includes Kraus and Stoll (1972a), who address the

[129] Recent literature continues to provide empirical support to this anomaly. Examples are Lee and Swaminathan (2000), Hong, Lim and Steim (2000), Patro and Wu (2004), De Bondt and Wolff (2004), Bange and Miller (2004), Nijman, Swinkels and Verbeek (2004), Chen and De Bondt (2004), and Karolyi and Kho (2004).

[130] Rationalists (e.g., Conrad and Kaul, 1998) consider the return of winners in the holding period equal to their unconditional expected rates of return. Hence, the returns of the momentum portfolio should be positive after the holding period as well.

question of a parallel trading by institutions but find little evidence, Friend, Blume and Crockett (1970), who find mutual funds managers imitate successful funds, what leads to herding and positive-feedback trading, and Gwynne (1986), who documents herd behavior in banks' lending policies. Herding is related to social contagion (Shiller, 2000a). Nonetheless, it might be rational from the perspective of managers who are concerned about their reputations in the labor market (Scharfstein and Stein, 1990). Incentives to herd may arise endogenously since agents herd to mimic their more skilled counterparts (Trueman, 1994, Clement and Tse, 2005), they perceive it to be a safe course of action[131] (Jegadeesh and Kim, 2010) or because they herd on non-informative signal (DeLong et al. 1990a). Prendergast and Stole (1996), on the contrary, suggest newcomers will exaggerate their differences with others to appear talented —an anti-herding behavior that would be related to a cognitive dissonance reduction.

The first authors to model herd behavior were Scharfstein and Stein (1990) and Banerjee (1992) —see Chapter 3. A classic approach includes some theoretical models that predict low-reputation analysts are more likely to herd. Some examples are Lakonishok et al. (1992), Grinblatt et al. (1995), Trueman (1994) and Clement and Tse (2005). Other articles conclude analysts herd towards consensus. Thus, Wermers (1999) finds evidence of herding in mutual fund trading of small stocks and by growth-oriented funds. Hong et al. (2000) find experienced analysts are more likely to provide bold forecasts, while inexperienced analysts deviate less from consensus in order not to lose their jobs. Gallo, Granger and Jeon (2002) show agents conform to the macroeconomic consensus. Finally, Lamont (2002) notes agents produce more radical —and generally less accurate— forecasts as they become more established. Welch (2000) criticizes the literature above, warning that without knowing the underlying information flow, one cannot determine whether similar reports are due to a similar underlying information or is caused by mutual imitation. Zitzewitz (2001) proposes a statistical inference across a set of observations to solve the problem and finds analysts do not herd, but rather that they exaggerate their differences. Bernhardt, Campello and Kutsoati (2006) and Chen and Jiang (2006) get similar results supporting an anti-herding behavior when they consider analysts may extract information from consensus forecasts.

Jegadeesh and Kim (2010) take note of the criticism. First, they note the critique also has a flaw: it assumes consensus forecasts are unbiased, contrarily to empirical evidence.[132] Then, they implement a test to see whether analysts herd around the consensus when they make stock recommendations, and find some results consistent with the herding hypothesis. First, recommendation revisions are partly driven by herding, with stronger effects for downgrades than for upgrades (analysts are more reluctant to stand out from the crowd when they convey negative information). Second, market reaction to revisions are stronger when revised recommendations move away from the consensus. Third, analysts from larger brokerages are more likely to herd, supporting the prediction by Prendergast and Stole

[131] If their predictions turn out to be wrong when they herd, then their competitors would be wrong as well.

[132] Richardson, Teoh and Wysocki (2004) find consensus forecasts are initially optimistic, but gradually become pessimistic.

(1996). Four, analysts following stocks with small dispersion of opinions and those who make infrequent revisions are more likely to herd. Alternatively, Hwang and Salmon (2004) develop a new method to measure herding by investors: the cross-sectional evolution over time in factor sensitivities (e.g., CAPM betas) is analyzed, and deviations from equilibrium beliefs expressed in market prices quantified. Their study identifies that periods of market stress were critical turning points where herd behavior diminished and market efficiency was enhanced.

E. Predictability of returns

As we saw in Chapter 2, classic tests on EMH evidence stock returns may exhibit long-term predictability in time series, cross-sectional analysis and event studies. Regarding serial predictability, the classic approach focuses on dividend yields: for instance, Fama and French (1988b) find that the *dividend-to-price ratio* explains part of the returns over the subsequent four years. Regarding cross-sectional averages, the size effect (Banz, 1981) and *scaled-price ratios* such as earnings-to-price (Basu, 1977), book-to-market (Stattman, 1980), and debt-to-equity (Bhandari, 1988) have shown to have some predictive power. Event studies include earnings announcements (e.g., Bernard and Thomas, 1989), stock repurchases (Ikenberry et al., 1995), stock splits (Ikenberry et al., 1996), dividend initiations and omissions (Michaely et al., 1995), and IPO-related pricing anomalies (Ritter, 1991), which Barberis and Huang (2008) explain using prospect theory and mental accounting.

F. Financial puzzles

Equity premium puzzle – The average return on stocks has historically far exceeded the average return on risk-free debt. Mehra and Prescott (1985) analyze the ninety-year period 1889–1978 and find the average real annual yield on the Standard and Poor's 500 index was seven percent, while that on short-term debt was less than one percent. They show this differential cannot be explained by models in the Arrow–Debrew set up under the standard expected utility maximizing paradigm. This anomaly is known as the *equity premium puzzle*. Early models that explain the anomaly are DeLong et al. (1990a) and Epstein and Zin (1990).

Currently, behavioral finance provides two interpretations of this puzzle (Barberis and Thaler, 2003), one based on prospect theory and the other on ambiguity aversion. In regards to prospect theory, Benartzi and Thaler (1995) identify two factors that contribute to investors' reluctance to bear the risks associated with equities: loss aversion and narrow framing —a short performance evaluation period. When investors exhibit this combination, known as *myopic loss aversion*, the size of the equity premium is consistent, because under the presence of loss aversion, the aggregation rules of mental accounting are not neutral.[133] A similar approach is in Barberis et al. (2001) and Barberis and Huang (2007). Models

[133] Samuelson (1963) provides a classic example: He offered some colleagues to bet $200 to $100 that a side of a coin would not appear at the first toss. One of them replied he didn't bet 'because I would feel the $100 loss more than the $200 gain' (i.e., loss aversion), but that he would bet 'if you let me make 100 such bets'. Samuelson proves then a theorem: *"a person whose*

based on ambiguity aversion, instead, analyze how people react to ambiguity. Weitzman (2007) shows risk seems larger under structural uncertainty. One quantitative implication is that agents may have a reference probability distribution in mind, but they make decisions according to a 'worst-case misspecification' scenario. Maenhout (2004) shows that, if investors are worried about the possibility that their model of stock returns is misspecified, they will require a higher equity premium as a compensation for the ambiguity in the probability distribution. His results, nonetheless, suggest ambiguity aversion would only be a partial explanation for this puzzle.

Stock market participation puzzle – Related to the equity premium puzzle, Barberis et al. (2006) define this puzzle as the fact that, even though stock markets have a high average return and a low correlation with other risks, many households are reluctant to allocate any money in it. They reckon Mankiw and Zeldes (1991) to be the first to study this puzzle. Barberis and Huang (2007) suggest narrow framing might predict what kinds of people are more likely to participate in stock markets.

Forward premium puzzle – In currency markets, the forward premium —the difference between the forward and the spot exchange rates— negatively forecasts changes in the exchange rate, an anomaly known as the forward premium puzzle (Burnside et al., 2011). Empirical studies (e.g. Hodrick, 1987) show that, when short-term nominal interest rates are high in one currency relative to other, the currency subsequently appreciates on average, which contradicts rational expectations models. Froot and Thaler (1990) claim the bias is due to expectation errors, not time-varying rational premia for systematic risk (Fama, 1984). Burnside et al. (2011) interpret the puzzle as a consequence of overconfident investors overreacting to a positive signal about the future money growth differential.

Closed-end fund puzzle – A closed-end fund is a mutual fund that issues a fixed number of shares that are traded on the stock market. The closed-end fund puzzle is the empirical finding that closed-end fund shares typically sell at prices not equal to the per share market value of assets the fund holds. Lee, Shleifer and Thaler (1991) show that discounts of 10 to 20 percent have been the norm. The puzzle is often related to the existence of limits of arbitrage. For instance, Pontiff (1996) finds the market value of a fund is more likely to deviate from fundamentals when portfolios are difficult to replicate, funds pay smaller dividends, funds have lower market values, or when interest rates are high, consistent with noise trader models of asset pricing (e.g., DeLong et al., 1990a).

---

utility schedule prevent him from ever taking a specific favorable bet when offered only once can never rationally take a large sequence of such fair bets, if expected utility is maximized" (p. 109). However, things are different under prospect theory. If Samuelson's colleague had a value function that exhibits loss aversion (e.g., $V(x)$ = [x if x>0, 2.5x if x<0], where x is change in wealth relative to the status quo), he would turn down one bet but accept two or more *as long as he did not have to watch the bet being played out.* Indeed, one toss yield an expected value of ($200 * .5) – (2.5 * $100 * .5) = -$25 but, since the distribution of outcomes with two consecutive bets is [$400, .25; 100, .50; -$200, .25], the expected value is ($400 * .25) + ($100 * .5) – (2.5 * $200 * .25) = $25. Hence, when decision-makers are loss averse, they will be more willing to take risks if they evaluate their performance infrequently. Benartzi and Thaler (1995) interpret the equity premium puzzle the same way: *"The attractiveness of the risky asset will depend on the time horizon of the investor. The longer the investor intends to hold the asset, the more attractive the risky asset will appear, so long the investment is not evaluated frequently"* (p. 75).

G. Anomalies in corporate finance

Dividend puzzle – Firms paying dividends is the main puzzle behavioral corporate finance has tried to solve (Thaler, 1993). The Modigliani–Miller theorem (Modigliani and Miller, 1958, 1959; Miller and Modigliani, 1961) claims a dividend policy irrelevance: a stock that pays dividend should be similar to another that pays no dividend —ignoring transaction costs and taxes— since the price of the dividend-paying stock drops on the ex-dividend date by the same amount. The dividend policy of a company does not affect its value because the higher the dividend, the lower the capital appreciation (Black, 1976). However, Black notices a *dividend puzzle*: companies do pay dividends, and investors do care for them. Shefrin and Statman (1984) first suggested that the tendency of investors to favor cash dividends could be explained by behavioral and cognitive elements in terms of two new theories of choice at that time: the theory of self-control (Thaler and Shefrin, 1981) and the prospect theory (Kahneman and Tversky, 1979). Miller (1986) does not agree, finding the anomaly is a misinterpretation of the basic model.

High rates of business failure – A classic empirical result is that most new businesses fail within a few years (Camerer and Lovallo, 1999). Examples are Dunne, Roberts and Samuelson (1988) and Baldwin (1995). Some standard features that explain the chances of business failure and survival are firm's size and industry concentration (for a review, see Geroski, Mata and Portugal, 2010). However, this does not explain why so many entrepreneurs keep on trying to start new business and fail. The behavioral interpretation to this anomaly was provided by Camerer and Lovallo (1999). They set the hypothesis that the high rates of business failure are a result of excessive optimism about the future and overconfidence on relative abilities (i.e., the better-than-average effect). Camerer and Lovallo provide experimental evidence of this hypothesis. Rodrigues, Da Costa and Da Silva (2011) replicate the experiment by Camerer and Lovallo (1999) to consider managers as well as students, and find that managers are more prone to feature the overconfidence and excess entry relationship than students.

High rates of M&A – As described in Chapter 3, a classic puzzle in corporate finance is the high rates of mergers and acquisitions observed, despite they do not allow acquiring firms to earn superior returns after the takeover. Roll (1986) suggested the hubris hypothesis of corporate takeovers, while Shleifer and Vishny (2003), on the contrary, suggest managers are rational and take advantage of market inefficiencies through merger transactions. CEO overconfidence is also a classic argument (Malmendier and Tate, 2008; Liu and Taffler, 2008). Other articles include Malmendier, Tate and Yan (2011).

Corporate diversification – There is evidence that multi-segment firms trade at a discount compared with a portfolio of single-segment firms (Lang and Stulz, 1994). Hence, there is a debate on whether diversification destroys shareholder value (Andreou et al., 2012). Again, a classic behavioral interpretation is based on overconfidence: Malmendier and Tate (2008) find that overconfident CEOs overestimate their ability to generate returns and, as a result, tend to be more acquisitive, overpay for acquired firms and, on average, destroy shareholder value mainly through diversification deals.

4.3.2. Decision effects

A second category of behavioral consequences are investor behavior anomalies —we denote decision effects. Behavioral biases affect people in a way they cause effects not predicted by the classic paradigm. This is a most complex category to determine which topics should be included. Whether a particular behavior is a decision effect or, alternatively, a heuristic, a judgmental bias or a social factor is sometimes not clear. Some examples follow to illustrate. Authors like Rabin (1998) and Hens and Bachmann (2008) classify the endowment effect and the status quo bias as heuristics; others instead (e.g., Kahneman et al., 1991; Novemsky and Kahneman, 2005) consider them effects of loss aversion (indeed Novemsky and Kahneman call the endowment effect a riskless loss aversion). Regret is an emotion that may be seen as a bias, or even an emotional factor related to social relations (do we feel regret because we made a bad choice or because other people know we made a bad choice?). However, since it is a feeling we feel *after* a decision has been made, it better fits as a decision effect.[134] In addition, some concepts are clearly related to others already described, such as investors' excessive trading and the excessive trading volume anomaly. Nonetheless, some other concepts, such as the investors' preference for dividends, portfolio underdiversification or window dressing, are clear examples of effects that are a consequence of investor behavior. The main decision effects are summarized in Table 4.7 and reviewed below.

TABLE 4.7 – Decision effects

DECISION EFFECTS	Related Effects and Concepts	CAUSAL FACTORS	Notes
ENDOWMENT EFFECT	STATUS QUO BIAS	Loss aversion	*Endowment (Thaler, 1980); Status quo (Samuelson & Zeckhauser, 1988) Some authors (Rabin 1998) consider them Heuristics. Most authors (e.g., Tversky and Kahneman, 1991) consider them effects of loss aversion*
DISPOSITION EFFECT	Underreaction	Loss aversion	*A.k.a. 'Try-to-break-even' effect, it explains underreaction to information and profitability of momentum strategies (Grinblatt & Han, 2005)*
	Momentum	Mental accounting	*Loss aversion and Mental accounting explain it (Shefrin and Statman, 1985)*
REGRET	COGNITIVE DISSONANCE		*Regret related to cognitive dissonance and prospect theory (Shiller, 2000a)*
	Psychological call option	Regret aversion	*Hens and Bachmann (2008)*
PORTFOLIO UNDERDIVERSIF.	HOME BIAS - Local bias	Familiarity	*Familiarity (Cao et al. 2011); Framing (Shefrin & Statman 2000); Home bias (French & Poterba, 1991); Prospect th. (Barberis & Huang 2008)*
	Naive diversification	Framing, Prospec theory	*Naive diversification (Benartzi & Thaler 2001)*
Money illusion		Framing	*Kahneman et al. (1986a)*
House money effect		Mental accounting	*Thaler and Johnson (1990)*
Disjunction effect			*Shiller (2000a)*
Habit formation			*Hens and Bachmann (2008)*
Window dressing			*Lakonishok et al. (1991)*
Illusion of knowledge	Overconfidence		*Barber and Odean (2002)*
Omission bias			*Hirshleifer (2008)*
Reference group neglect			*Camerer and Lovallo (1999)*
Scapegoating and Xenophobia			*Hirshleifer (2008); Aronson et al. (2006)*
Sensation seeking			*Grinblatt and Keloharju (2009)*

Source: Own elaboration

[134] Nonetheless, before making a decision we may exhibit regret aversion —i.e., a judgmental bias (e.g., Zeelenberg et al., 1996).

A. Endowment effect

Thaler (1980) denominates *endowment effect* the increased value of a good when it becomes part of an individual's endowment. It represents a consequence of loss aversion (Tversky and Kahneman, 1991), since the loss of utility when giving up a good is greater than the utility of receiving it. Kahneman *et al.* (1990) describe it as willingness to accept (WTA) being greatly larger than willingness to pay (WTP), a discrepancy the Coase theorem cannot explain.[135] Knetsch and Sinden (1984) were the first to provide experimental evidence of this disparity between WTA and WTP. Two alternative explanations are a search for evidence of sustitability, a rational hypothesis,[136] and the status quo bias —a behavioral hypothesis. Kahneman et al. (1990) confirm experimentally the endowment effect and status quo bias are manifestations of loss aversion. Horowitz and McConnell (2003) use WTA/WTP ratios from a dataset of 201 experiments to calculate the income effect —defined as the change in WTP for the good in question when the income increases, ∂WTP/∂y— to conclude they are too high to be consistent with neoclassical preferences.

Status Quo effect – In decision making, people often choose the status quo alternative: do nothing or maintain one's previous decision (Samuelson and Zeckhauser, 1988). Often referred as the status quo bias, we might have classified it in the heuristic-and-biases category, related to the familiarity bias (e.g., Hartman, Doane and Woo, 1991). However, most literature relate it to the endowment effect. Thus, Samuelson and Zeckhauser (1988) say an antecedent for status quo bias is endowment effect, and Kahneman et al. (1991) and Tversky and Kahneman (1991) show that one implication of loss aversion, as with the endowment effect, is that people have a strong tendency to remain at the status quo, because disadvantages of leaving it overcome advantages.[137]

The effect was first demonstrated by Samuelson and Zeckhauser (1988), who implemented a series of decision problems followed by a set of mutually exclusive alternative actions from which to choose. The alternatives were framed in two ways: under a neutral framing, a menu of potential options with no specific labels attached was presented; under a status quo framing, one of the options was placed in the status quo position and the other became alternatives to the status quo.[138] The status quo

[135] The Coase theorem (Coase, 1960) says traders who can transact at no cost should allocate resources independent of their initial property rights. Kahneman *et al.* (1990) show instead that if the marginal rate of substitution between two goods is affected by endowment, traders who have an initial property right will be more likely to retain it.

[136] Hanemann (1991) proves that the difference between WTP and WTA depends on the ratio 'income elasticity of demand for the good to elasticity of substitution between the good and a composite commodity'. When the elasticity of substitution is low, the ratio will be large, and so the WTA/WTP ratio.

[137] The status quo may be seen as the reference point, so the individual would weigh potential losses from switching as well as potential gains. Since loss aversion determines losses are weighted heavier than gains, individuals would choose not to change. Notwithstanding, some other causes might induce a status quo bias in the absence of loss aversion. Samuelson and Zeckhauser (1988) explore some of them: rational decision making in the presence of transition costs and uncertainty, convenience, habit, policy or custom, regret avoidance, cognitive misperceptions (loss aversion, anchoring) and psychological commitment stemming from misperceived sunk costs, fear or innate conservatism, a drive for consistency, or even cognitive dissonance.

[138] In the first part of the questionnaire the status quo condition was framed by the wording of the decision problem made by the experimenters (i.e., the status quo was exogenously given). The second part, instead, involved sequential decisions where the subject's initial choice determined the status quo for a subsequent choice. No significant differences were obtained.

framing was found to have predictable and significant effects on participants' decision making. Other early works include Knetsch and Sinden (1984) and Knetsch (1989). Then, an initial attempt to study the bias in an economic context is in Hartman et al. (1991), who find empirical evidence of a status quo effect in consumer valuations of an unpriced product —namely, the demand for residential electricity. Fernandez and Rodik (1991) suggest a status quo bias appears when the identities of gainers and losers from a reform cannot be determined beforehand. Finally, Roca et al. (2006) show the effect emerges when people prefer an ambiguous alternative in their possession than an unambiguous one —a sort of ambiguity-seeking attitude that emerges with and without incentives.

B. Disposition effect

Coined by Shefrin and Statman (1985) and known as well as a try-to-get-even effect, it reflects the tendency of investors to sell winners (stocks whose price has increased) too early and ride losers too long —in order not to recognize a loss. The disposition effect has been related to pricing phenomena such as the post-earnings announcement drift and stock price momentum (Grinblatt and Han, 2005), and helps explain the excessive trading volume observed in stock markets (Odean, 1999). Some articles that find evidence of the effect are in order. Odean (1998a) computes the proportion of gains realized (PGR) and the proportion of losses realized (PLR)[139] and finds PGR = 0.148 significantly greater than PLR = 0.098 (with similar results for all months except December, when tax-motivated selling prevails). Grinblatt and Keloharju (2001) observe the two major determinants for investors to sell a stock are reluctance to realize losses and tax-loss selling. Other determinants of trading are reference price effects and the smoothing of consumption according to the life-cycle hypothesis.[140] Statman et al. (2006) find overconfidence and disposition effect are more pronounced in small-cap stocks. Frazzini (2006) shows that investors displaying the disposition effect induce a price underreaction to news announcements, leading to return predictability (post-earnings announcement drift). Finally, Chen et al. (2007) find a stronger disposition effect for Chinese investors than for Americans.

The most plausible explanations for the disposition effect are prospect theory, particularly loss aversion, and mental accounting (Shefrin and Statman, 1985; Grinblatt and Han, 2005). Nonetheless, the evidence of a disposition effect is not universal. Shefrin and Statman (1985) suggest regret would explain why some individual investors do not display the effect, while self-control helps to explain how professional traders force themselves to realize losses. In addition, Barberis and Xiong (2009) extend Odean's (1998a) methodology to investigate whether prospect theory predicts the disposition effect in

[139] On any day an investor in the sample sells a share, every stock in the investor's portfolio is classified into one of four categories: a realized gain or realized loss is counted if the stock was actually sold (at a gain or loss), and a paper gain or paper loss is counted for stocks that were not sold (but quote at a gain or loss from the purchase price). Then, the proportion of gains realized is defined as PGR = no. of realized gains / (no. of realized gains + no. of paper gains) and the proportion of losses realized as PLR = no. of realized losses / (no. of realized losses + no. of paper losses).

[140] Developed by Modigliani and Brumberg (1954), the hypothesis suggests rational agents should smooth their consumption by investing and borrowing based on expectations about their lifetime income (Grinblatt and Keloharju, 2001).

all circumstances, and find surprising results. If prospect theory is defined over realized gains and losses, results are consistent with a disposition effect. However, if preferences are defined over *annual* gains or losses and investors are allowed to trade several times a year, the results actually predict the opposite.

C. Regret

Bell (1982) describes regret as the emotion caused by comparing a given outcome with the state of a foregone choice. Alternatively, it is the pain we feel when we realize we would be better off today had we chosen another option in the past (Barberis and Huang, 2009). Kahneman and Riepe (1998) highlight people feel more regret about things they did, but they feel regret of things they did not, too. This is called regret of omission, and people who exhibit this feeling have a tendency to take more risks. Gilovich, Medvec and Kahneman (1998) debate on whether people regret actions more in the short term and inactions in the long run —something Kahneman disagrees. To solve the controversy, three empirical tests were performed and established some common ground.[141]

Regret is related to cognitive dissonance and it is also embodied in prospect theory, in the notion of a kink in the value function at the reference point (Shiller, 2000a). Regret avoidance helps to explain the disposition effect. Inman and McAlister (1994) find regret influences coupon redemption patterns in the bond market. Regret has been also related to the psychological call option (Hens and Bachmann, 2008) and narrow framing (Barberis and Huang, 2009). Finally, Pan and Statman (2010) suggest that investors' risk tolerance assessed in hindsight amplifies regret: investors often claim, in hindsight, that advisors overstated their risk tolerance and they were induced to undertake unsuitable investments.

Cognitive dissonance – When two simultaneously held cognitions are not consistent, it produces a state of cognitive dissonance (Festinger, Riecken and Schachter, 1956). This makes people feel internal tension and anxiety, so they will strive to reduce it either changing past values, feelings and opinions, or attempting to justify or rationalize their choice. According to a theory of self-perception, major cognitive dissonance phenomena may be seen as interpersonal judgments in which the observer and the observed happen to be the same person (Bem, 1967). Goetzmann and Peles (1997) argue cognitive dissonance would explain why investors switch to winning mutual funds more rapidly than they flow out of losers. A similar interpretation is in Ricciardi and Simon (2000), who highlight people tend to change their investment styles or beliefs to support their financial decisions. Finally, Daniel *et al.* (1998) relate cognitive dissonance and self-attribution bias.

Psychological call option – Hens and Bachmann (2008) suggest investors may hire a financial advisor not (only) for advice, but because if their investments yield a satisfactory return the investors attribute it to their skills, but if it turns out to be wrong, they lower regret by blaming the advisor.

[141] When we feel regret for something we did, hot emotions (anger, shame...) are elicited. Inaction regrets elicit wistful emotions (nostalgia) —as Kahneman argues— as well as despair (misery) —as Gilovich and Medvec suggest.

D. Portfolio underdiversification

Many researchers have documented the investors' tendency to hold portfolios made up of far fewer securities than necessary to eliminate idiosyncratic risk (e.g., Odean, 1999; Benartzi and Thaler, 2001; Goetzmann and Kumar, 2008). A number of papers, including Statman (1987) and Meulbroek (2005), show empirically this failure to diversify is costly in terms of the risk-return tradeoff achieved. All theoretical explanations for this behavior have a common link: the desire for upside potential is a driving factor (Mitton and Vorkink, 2007). These include a stronger preference for skewness (Arditti, 1967; Simkowitz and Beedles, 1978), framing (Shefrin and Statman, 2000), prospect theory (Polkovnichenko, 2005; Barberis and Huang, 2008), investor overconfidence (Goetzmann and Kumar, 2008; Anderson, 2012) and familiarity bias (Grinblatt and Keloharju, 2001; Cao et al., 2011). Kumar and Lim (2008) predict investors that trade several times a day should exhibit weaker disposition effect and have better diversified portfolios. Benartzi and Thaler (2001) observe a *naïve diversification*: people do diversify but in a naïve fashion, like allocating 1/n of their savings amongst *n* investment options, no matter which they are or of which risk profile. Finally, home and local bias are a classical expression of this investor behavior. We see them next.

Home bias – First reported by French and Poterba (1991), who show U.S., Japan and U.K. investors allocate 94%, 98% and 82% of their equity investments in domestic securities, the bias is suggested to stem from a familiarity bias (Cao et al. 2011) and ambiguity aversion (Hens and Bachmann, 2008). Ackert et al. (2005) provide experimental evidence of the familiarity bias interpretation. Evidence of a home bias in the banking industry is suggested by De Haas and van Horen (2011), who show banks with head offices farther away from their customers are less reliable funding sources during a crisis, and Presbitero, Udell and Zazzaro (2012a,b), who show the credit crunch in Italy was harsher in provinces with a large share of branches owned by distantly-managed banks.

Local bias – An analog to home bias but within countries. Examples of this bias include Grinblatt and Keloharju (2001), who find evidence of it amongst Finnish investors, Cao et al. (2011), Ackert et al. (2005), and Huberman (2001), who provides evidence of a local bias using data on the geographical distribution of the shareholders of seven regional bell operating companies in the U.S.

E. Other effects

Money illusion – An effect derived from framing, it implies people pay more attention to nominal rather than real changes in economic variables such as wages or prices (Kahneman et al, 1986a).

House money effect – Many investors, after making some money with their investments, tend to exhibit an increased risk seeking attitude (Thaler and Johnson, 1990). This leads them to increase their willingness to gamble with the money they have recently won (Hens and Bachmann, 2008), clearly an effect consequence of mental accounting.

Disjunction effect – Shiller (2000a) define it as the tendency to wait to make decisions until some information is revealed, even if it is not relevant and we would make the same decision regardless of the information. It represents a contradiction to the "sure-thing principle" of rational behavior (Savage, 1954). Tversky and Shafir (1992) provide empirical evidence.

Window dressing – The practice of adding winners and eliminating losers in professionally managed portfolios, especially at dates like year end, in order to *remove embarrassments* from reports. Lakonishok et al. (1991) find evidence of this practice in the fourth quarter and across small funds.

Omission bias – Following Ritov and Baron (1990), it is the tendency to favor omissions (such as letting someone die) over otherwise equivalent commissions (such as killing someone). Omission bias would explain why students of economics find the concept of opportunity cost surprising.

Reference group neglect – Camerer and Lovallo (1999) observe that self-selected subjects seem to neglect they are competing with a group of subjects who think they are skilled too. They compare it to the neglect of adverse selection that leads to a winner's curse in bidding.

Scapegoating and Xenophobia – People tend to prefer members of their own group to outsiders, a phenomenon called in-group bias (Hirshleifer, 2008). When this bias causes fear or hostility toward strangers or foreigners, we are dealing with xenophobia. Scapegoating refers to the tendency of individuals to look for someone to blame when things go wrong (Aronson, Wilson and Akert, 2006). Blame is generally laid upon some visible, disliked, and relatively powerless groups.

Sensation seeking – First described by Zuckerman, Eysenck and Eysenck (1978), Grinblatt and Keloharju (2009) define it as a measurable psychological feature related to gambling, risky driving, risky sexual behavior, drug and alcohol abuse and others. It would be more frequent in men and decreasing with age (Zuckerman et al., 1978), and a motivator for trade in financial markets, according to Grinblatt and Keloharju, who obtain empirical evidence.[142]

[142] In addition, many other biases and anomalies can be found in literature. The list would be endless, but a tentative list would include concepts such as bandwagon effect (Nadeau, Cloutier and Guay, 1993), barn door closing (Zeckhauser, Patel and Hendricks, 1991), bias blind spot (Pronin and Kugler, 2007), certainty effect (Tversky and Kahneman, 1986), default effect (Johnson and Goldstein, 2003), clustering illusion (Gilovich, 1991), denomination effect (Raghubir and Srivastava, 2009), disappointment aversion (Gul, 1991), egocentric bias (Greenberg, 1983), elicitation effects (which, according to Rabin (1998), would include framing effects, preference reversals and context effects), false consensus (Ross, 1977), false memory and suggestibility (Roediger and McDermott, 1995), habit (Raghubir and Ranjan Das, 1999), halo effect (Nisbett and Wilson, 1977), illusion of knowledge (Barber and Odean, 2002), illusory correlation (Tversky and Kahneman, 1974), magical thinking (Shiller, 2000a) and quasimagical thinking (Shafir and Tversky, 1992), manias (Kindleberger, 1978), mood effects (Hirshleifer, 2008), motivated cognition (Kruglanski et al., 2012), negativity or pessimism bias (Mansour, Jouini and Napp, 2006), out-group bias (Aronson et al., 2006), outrage heuristic (Sunstein, 2005), panics (Ricciardi and Simon, 2000), persuasion effect (Petty and Briñol, 2008), regret aversion or regret avoidance (Zeelenberg et al., 1996), reward pursuit (Bijleveld, Custers and Aarts, 2012), salience and vividness (Hirshleifer, 2008), self-deception (Trivers, 2011), sign effect (Thaler, 1981), similarity heuristic (Rozin and Nemeroff, 2002), snake-bite effect (Thaler and Johnson, 1990), tallying (Marewski et al., 2010), unpacking effect (Van Boven and Epley, 2003), winner's curse (Thaler, 1992) and many others.

4.4. CONCLUDING REMARKS

We have provided an extensive review of the main biases and anomalies in the literature. The main purpose of this review is to have a better criterion to select which will be the main lines of research in Part III of this thesis. In particular, we are in search of the psychological biases that have been attributed greater importance in the interpretation of investor and market anomalies. These are the main results we have obtained.

First, we distinguish two broad categories: psychological biases and behavioral consequences. The former imply a predisposition toward error, while the consequences of those biases, either market anomalies or decision effects, are empirical results that are difficult to rationalize.

Second, among the psychological biases, the taxonomy we provided differentiates four groups: heuristics and biases, framing, valuation and errors of preference, and social factors. Among them, representativeness, overconfidence, prospect theory and social contagion are perhaps the most recurrent. Surely, the leading role of prospect theory is beyond doubt, being the most relevant descriptive theory of decision making under uncertainty.

Third, behavioral consequences may refer to decision effects (related to individuals) or to market anomalies. Again, the causal factors behind the most relevant effects and anomalies confirm the importance of representativeness and overconfidence in belief formation, and social contagion in herd behavior. Overconfidence, in particular, is one of the most relevant heuristic-driven biases which has been claimed to play a significant role in corporate management anomalies, as well as in significant market anomalies such as excessive trading volume, over and underreaction.

In consequence, for the purposes of this thesis we will focus on overconfidence and prospect theory. Chapter 5 will provide deeper insight on these two areas of the literature, as well as an extended vindication of our choice, to finish Part II.

CHAPTER 5. PROSPECT THEORY AND OVERCONFIDENCE

5.1. INTRODUCTION

In Chapter 4 we offered a taxonomy, summarized in Table 4.1, of the main behavioral biases and anomalies identified in the academic literature. The former are classified into heuristics and biases, framing, valuation/errors-of-preference and social factors, and the latter may refer to decision effects or to market anomalies. Inside each category we may find dozens of biases and anomalies that challenge the basic tenets of traditional finance. Notwithstanding, in this thesis we will focus on two areas: prospect theory (Kahneman and Tversky, 1979) and overconfidence (Moore and Healy, 2008).

The reason why we choose these two areas is threefold. First, they are two of the most-well studied areas in behavioral finance. Second, both concepts have been suggested to explain a risk-seeking behavior by market participants. Third, key concepts in prospect theory —like loss aversion or diminishing sensitivity— as well as overconfidence might help explain how misperceptions by participants in the banking sector might have led them to engage in inappropriate credit policies. Both areas will be the basis for the theoretical and experimental research in Part III. In particular, the theoretical models in Chapter 9 assume the existence of at least one boundedly rational bank that is distorted by overconfidence, while the experimental research in Chapters 7 and 8 analyzes the effects that different risk profiles according to prospect theory, as well as different measures of overconfidence, may have over banks' credit policies and performance.

Thus, this chapter is devoted to provide further insight on overconfidence and prospect theory, with a focus on some aspects (different measures and calibration of parameters) that will be required later in the experimental research. Chapter 5 is organized as follows. Sections 5.2 to 5.4 are devoted to prospect theory: we firstly review the importance of prospect theory in the literature, then we provide an extensive insight on prospect theory and the parametric specifications we will use, finally we analyze how to elicit those parameters in a way we will do it in the experimental setting. Sections 5.5 to 5.7 are devoted to overconfidence: following a similar structure, we first review its importance in the literature, then we provide extensive insight into the theory of overconfidence by Moore and Healy (2008) and the three basic measures they suggested, while in the latter subsection we explain how the three measures of overconfidence are to be estimated, in order to use them in the experimental setting.

5.2. PROSPECT THEORY IN THE LITERATURE

A common taxonomy in social sciences divides theories into normative and descriptive (a.k.a. positive). Normative theories set rules about the optimal behavior of individual decision makers (i.e., how should a rational agent behave), while descriptive theories are focused on identifying how real people actually behave. In the context of decision theory, the expected utility theory (EUT) is the most accepted normative model, while prospect theory (PT) is the most well-known descriptive theory. Understanding how prospect theory challenges EUT requires a background on several related concepts (such as axioms of rationality, risk measurement, stochastic dominance and risk-aversion). Therefore, we start with a review of the expected utility theory and continue with prospect theory afterwards.

Expected utility theory

Three postulates on which the main pillars of standard finance were built are rational expectations, the expected utility theory, and market efficiency. According to Barberis and Thaler (2003), standard finance's *rationality* means two things: first, agents are Bayesian, meaning they update their beliefs when new information comes to the market according to the Bayes' rule

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}\ , \tag{5.1}$$

where A and B are events and $P(\cdot|\cdot)$ is a conditional probability. Second, agents' choices are consistent with Savage's notion of subjective expected utility (Savage, 1954). The EUT, for its part, was accepted as a normative model of rational choice under risk since the theorem of von Neumann and Morgenstern (1944). The theorem is derived from a set of axioms required to make rational decisions, namely, that preferences[143] must be complete, transitive, continuous, and satisfy the independence axiom. The theorem states that a preference order that is complete, transitive and continuous can be represented by an expected utility function[144] if and only if the preference order satisfies the independence axiom[145].

143 Following Hens and Bachmann (2008), a *preference* is a binary relationship on a choice set X. Given two alternatives $x, y \in X$, a preference $x \succcurlyeq y$ means alternative x is at least as good as alternative y, $x \succ y$ means x is strictly preferred, and $x \sim y$ means both alternatives are equally good. A preference relation is *complete* if for all alternatives in the choice set the individual has a well-defined preference. Besides, it is *transitive* if for all $x, y, z \in X$, if $x \succcurlyeq y$ and $y \succcurlyeq z$, then $x \succcurlyeq z$ holds. Finally, preferences are representative of a rational choice, and a utility function exists such that it describes those preferences, if the preference relation on X is *continuous*: for all lotteries x, y and z, $x \succ y \succcurlyeq z$ there exists a coefficient $\alpha \in (0, 1)$ such that $\alpha \cdot x + (1-\alpha) \cdot z \succ y$. That is, preferences do not exhibit erratic behavior like sudden jumps caused by minor changes in data, nor there are alternatives that are infinitely better or worse than others as to *poison* any compound alternative in which it is included. Completeness, transitivity and continuousness ensure a preference relation can be assigned numerical values (i.e., a *utility function*) to the outcomes of different alternatives in order to compare them.

144 That is, a utility function satisfies that $x \succcurlyeq y \leftrightarrow E_u(x) > E_u(y)$.

145 The *independence axiom* is satisfied if for all lotteries (being a lottery a set of consequences and the probability thereof) x, y and z, and for all numbers $0 \leq \alpha \leq 1$, we have $x \succcurlyeq y$ if and only if $\alpha \cdot x + (1-\alpha) \cdot z \succcurlyeq \alpha \cdot y + (1-\alpha) \cdot z$. That is, if one lottery is preferred to another, and we mix both with the same third one, the preference ordering is independent of the particular third lottery used. Then, if preferences —besides being complete, transitive and continuous— satisfy the independence axiom, they can be represented by an *expected utility function*, where the expected utility of a lottery is the sum of utilities derived from each of the consequences the lottery offers, weighted with their probabilities.

Decision making under risk can be viewed as a choice between prospects or gambles. Thus, when describing decision making under risk we must analyze stochastic dominance.[146] EUT defines utility in terms of total wealth, such that marginally increasing a person's wealth always increases total utility ("more is preferred to less"), while it also uses variance as a risk measure, suggesting a rational decision-maker should weight negative returns equally with positive returns. Then, a fifth axiom for rationality would be to consider that the simplest case, known as state dominance, should hold as well: a lottery dominates another if the former gives a better outcome than the latter in any state of the world. State dominance is a special case of first order stochastic dominance[147] (FSD) that implies more is better and individuals should be indifferent to identical lotteries.

FSD implies preference: every expected utility maximizer with an increasing utility function will prefer lotteries that are FSD. Hadar and Russel (1969) introduce a weaker condition: second order stochastic dominance (SSD), which holds whenever the area under one cumulative distribution is equal to, or larger than, that under the other cumulative distribution —in which case the latter would dominate the former.[148] FSD implies SSD, but not vice versa. One implication of SSD is that the dominant distribution has a mean at least as large as the other distribution, and the former is more predictable (that is, it has a lower variance). Hence, SSD allows for comparison between the moments of two or more distributions. Hence, for SSD risk aversion plays a determinant role: all risk-averse expected-utility maximizers prefer a lottery that dominates another in the SSD sense. Modern Portfolio Theory (MPT), for example, assumes all investors are risk averse so they never choose a portfolio that has larger variance with the same mean return. Since SSD is a weaker condition than FSD, it is capable of ordering a large set of distributions, but it requires assuming the expected utility function is concave. Thus, in order to understand what that means, we need some insight on degrees of risk aversion.

Pratt (1964) and Arrow (1971) analyze utility functions and risk aversion. When comparing preferences, if an individual regards a certain payoff is as good as playing a lottery, such payoff is known as the *certainty equivalent*. The *risk premium* is the expected monetary value of the lottery minus the cash equivalent. *Risk aversion* measures this reluctance of a person to accept the lottery with the higher, but uncertain, payoff. Pratt measures local aversion to risk as the individual's risk premium for a small, actuarially neutral risk, known as the *Arrow–Pratt measure of absolute risk aversion* (ARA):

$$ARA(w) = -\frac{u''(w)}{u'(w)}, \tag{5.2}$$

[146] Early literature on stochastic dominance would include von Neumann and Morgenstern (1944), Markowitz (1959), Tobin (1958, 1965) and Hadar and Russell (1969), who provide a formal terminology.
[147] A prospect dominates another in the first order stochastic dominance sense if the value of the cumulative distribution of the preferred prospect never exceeds that of the inferior prospect (Hadar and Russell, 1969).
[148] If the random variable is continuous, then the following must hold: $\int_{x_1}^{x} G(y)dy \leq \int_{x_1}^{x} F(y)dy$ for all $x \in I$, being I the closed interval $x_1 - x_n$ of possible values taken by the random variable.

where w is total wealth, and $u''(\cdot)$ and $u'(\cdot)$ are the second and first derivatives of the utility function, $u(\cdot)$.[149] Pratt (1964) concludes that *"the aversion to risk implied by a utility function u(·) seems to be a form of concavity, and one might set out to measure concavity as representing aversion to risk" (p. 127)*. The prevalence of risk aversion is the best known generalization regarding risky choices, and led early decision theorists to propose that utility is a concave function of money (Kahneman and Tversky, 1979). An additional measure, *relative risk aversion* (RRA), was then introduced to solve a problem with ARA: RRA has the advantage that it is still a valid measure of risk aversion even if the utility function changes from risk-averse to risk-loving as wealth changes.[150] It is obtained by multiplying ARA with wealth:

$$RRA(w) = -w \cdot \frac{u''(w)}{u'(w)}. \tag{5.3}$$

Finally, intertemporal decision making helps to understand how preferences among lotteries are determined. When a financial decision includes future variables, people compare the utility they expect to receive. Rational evaluation assumes exponential discounting: future utilities are discounted by a weight that is an exponentially declining function of time (Hens and Bachmann, 2008). This implies time consistency: if we prefer \$100 now than \$110 within a week, we should also choose \$100 in 9 weeks than \$110 in 10. If not, we would exhibit a *preference reversal*, inconsistent with inter-temporal rational expectations as here defined. Kahneman and Tversky (1979) and further research by behaviorists came to highlight that, in practice, individuals do not behave as the EUT suggests,[151] violating some of the axioms above. They also provided an alternative model for choice under risk, known as prospect theory.

Prospect theory

In a series of experiments in the 1970s, Daniel Kahneman and Amos Tversky provided evidence that, when making decisions in a context of risk or uncertainty, most people show preferences that depend on gains and losses with respect to a certain reference point, and they form beliefs that do not correspond to the statistical probabilities —that is, their perception of the risks associated with a decision may be biased. Following this evidence, the authors introduced prospect theory (Kahneman and Tversky, 1979), today the most well-known descriptive decision theory. Prospect theory has two phases: in phase I a given decision problem is framed so it can be evaluated next; then, in phase II, after the decision problem has been framed, it is now evaluated. The way we calculate the utility of a lottery under EUT or under PT is different. Consider a simple binary lottery with payoffs $c_1 < c_2$ in the two states

[149] We can measure the degree of risk aversion by the curvature of the utility function. Thus, if it is concave, the higher the curvature the higher the risk aversion. We might use the second derivative $u''(\cdot)$ for such purpose, but such measure would not be invariant under positive affine transformations of the utility function (Hens and Bachmann, 2008). The simplest way to solve that is to use the ratio u''/u'. Now, if we change the sign we get the Arrow-Pratt measure of ARA.
[150] This way, if an agent has constant absolute risk aversion (CARA), she will not increase a single euro invested in risky assets as her wealth increases. On the contrary, an agent having constant relative risk aversion (CRRA) would increase the amount invested in risky assets as her wealth increases, so the share of wealth invested in risky assets remains constant.
[151] *"The modern theory of decision making under risk emerged from a logical analysis of games of chance rather than from a psychological analysis of risk and value. The theory was conceived as a normative model of an idealized decision maker, not as a description of the behavior of real people"* (Tversky and Kahneman, 1986, p. S251).

s=1 and s=2 of the world, and let p denote the probability of the first state. Then, the expected utility of this lottery will be given by

$$p \cdot u(W + c_1) + (1 - p) \cdot u(W + c_2)\,, \tag{5.4}$$

where W is current wealth. Prospect theory, instead, changes both the way utility is measured —providing a **value function** v(·) that is defined over changes in wealth— and the way subjects perceive the probabilities of the different outcomes —replacing p by some probability weightings w(p), as follows

$$w(p) \cdot v(c_1) + w(1 - p) \cdot v(c_2)\,. \tag{5.5}$$

Phase II evaluation problem is related to these value and **probability weighting function**. When individuals evaluate a prospect, they tend to (1) treat gains differently to losses, and (2) outcomes with smaller probabilities are over-weighted relative to more certain ones. In particular, Kahneman and Tversky (1979) presented several choice problems to highlight three effects inconsistent with the basic tenets of utility theory. These are the certainty, reflection and isolation effects:

- **Certainty effect**: people overweight outcomes considered to be certain. When a choice between a prospect and a sure gain is modified, such that the second choice involves a similar scenario but with both prospects being uncertain, people tend to change their decision, violating EUT.[152] For instance, given two choices

Choice 1:	A ($100, 0.80)	*vs.*	B ($75)
Choice 2:	C ($100, 0.20)	*vs.*	D ($75, 0.25)

  people tend to choose prospects B and C, a decision that contradicts EUT.[153]

- **Reflection effect**: the reflection of prospects around zero reverses the preference order. For instance, if we ask

Choice 3:	A' (-$100, 0.80)	*vs.*	B' (-$75)

  people tend to choose prospect A'. An important implication is that it explains why people may exhibit different risk profiles when facing gains or losses: risk aversion for gains and risk seeking for losses. In addition, the reflection effect eliminates aversion for uncertainty or variability as possible explanation for the certainty effect.[154] Rather than that, it appears that certainty increases the desirability of gains as well as the aversion to losses.

---

152 This is a variation of Allais paradox (Allais, 1953) that exposes the certainty effect among the respondents.
153 In particular, that decision contradicts the substitution axiom, which follows from the transitivity axiom. Prospect *A* should be preferred over *C* and *B* over *D* since they give the same outcome with greater probability (in fact, both cases in choice 1 were multiplied by the same probability p = 0.25 to obtain choice 2). If subjects choose B ≻ A, then it follows, substituting B ≻ D and A ≻ C, that D ≻ C when in fact they chose the opposite. Kahneman and Tversky (1979) provide here an empirical generalization: if $(y, p{\cdot}q)$ is equivalent to (x, p), then $(y, p{\cdot}q{\cdot}r)$ should be preferred to $(x, p{\cdot}r)$ for any probabilities p, q, r, $0 < p, q, r < 1$.
154 The former example between choices 1 and 2 would be explained by Allais (1953) or Markowitz (1959) as people comparing expected values and risk (variance): choosing prospect *B* would imply one prefers the prospect with no variance though its lower expected value, whereas choosing *C* would mean the difference in variance might be insufficient to overcome the difference in expected value. The reflection effect invalidates this possibility, since the contrary happens for negative outcomes.

- **Isolation effect**: there is empirical evidence that people discard elements shared by all prospects and focus on those that distinguish them —first analyzed by Tversky (1972). However, different decompositions may lead to different, inconsistent preferences. Consider for instance this sequential game:

> Nature moves first, with prob. p=0.75 you earn $0 and with (1-p) = 0.25 you go to a second stage where you must choose, before the game starts, between ($100, 0.80) and ($75) as in choice 1. What do you choose?

  This game and choice 2 above are equivalent, in the sense that probabilities of final states are identical. Nevertheless, most people that chose option C above now choose $75. This evidences a reversal of preferences: they ignored the first stage of the game, whose outcomes are shared by both prospects.

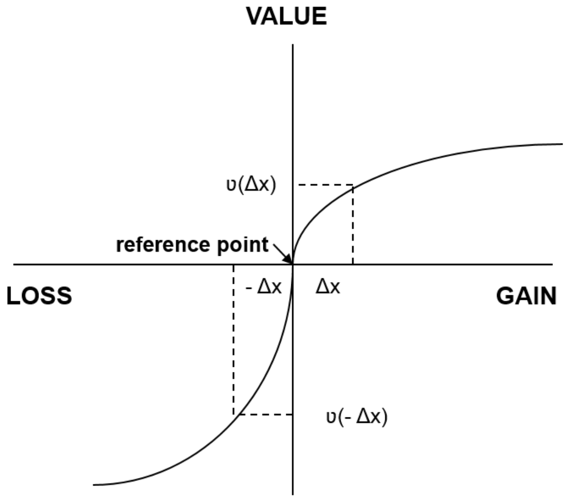
Based on these observations, Kahneman and Tversky (1979) offer a theory (PT) that is able to predict individual choices even in cases where the expected utility is violated. In PT the utility function is substituted by a value function that is defined over changes in wealth rather than over the final wealth. Such value function has 3 essential characteristics:

- **Reference dependence**: value is defined over gains and losses with respect to some *reference point*.
- **Diminishing sensitivity**: the marginal value of gains and losses decreases with size, resulting in a value function that is concave in gains and convex for losses.
- **Loss aversion**: the function is steeper for losses than for gains.

The carriers of value are changes in wealth, rather than final states. This is related to a debate between standard and behavioral finance about how risk is to be measured: the former considers risk has a neutral meaning associated with the uncertain (positive or negative) outcomes of decisions, so it is measured with volatility; behavioral finance claims instead that individuals perceive risk as losses with respect to a certain reference point. Reference dependence implies two things: individuals think in terms of *gains and losses* rather than total wealth, and whether a certain outcome is a gain or a loss depends on her reference point. The reference point is often assumed to be the status quo, for instance the current wealth level, implying it is a flexible reference (it may change over time). Diminishing sensitivity implies a different attitude towards risk: prospect theory predicts risk aversion in the domain of gains and *risk seeking* in the domain of losses (that is, people are willing to gamble only to avoid losses, exhibiting an *aversion to a sure loss*). Finally, the third property implies individuals making a loss of $100 need to gain more than $100 as compensation. Kahneman (2011) claims loss aversion is *"the most significant contribution of psychology to behavioral economics"* (p.300).

These properties result in a value function that is kinked at the reference point, concave above, convex below, and steeper in the negative domain, as in Figure 5.1.

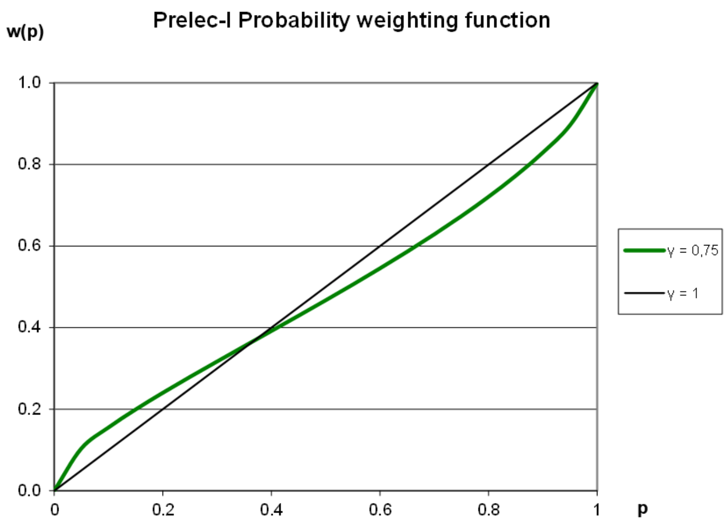
FIGURE 5.1 – The value function



Source: Own elaboration, based on Tversky and Kahneman (1992)

In addition, the objective probabilities are replaced by subjective decision weights. People usually do not treat probabilities linearly, but overweight rare events and underweight events with a higher probability. Hence, they evaluate risk using *transformed* rather than objective probabilities, where transformed probabilities are obtained by applying a weighting function, *w(p),* to the objective probabilities, such that low probabilities (close to 0 and 1) are over-weighted. It is important to notice the weighting function is not a subjective probability, but a distortion of a given probability: we know the probability of a fair coin landing on heads is 0.5, but in decision-making we might act as if probability were *w*(0.5). Figure 5.2 depicts a classic weighting function by Prelec (1998).

FIGURE 5.2 – The probability weighting function



Source: Own elaboration, based on Prelec (1998)

Experimental evidence confirmed a *fourfold pattern* of risk attitudes: risk aversion for gains and risk seeking for losses of moderate to high probability; risk seeking for gains and risk aversion for losses of low probability.[155] The value and weighting functions suggested by Kahneman and Tversky are able to explain that fourfold pattern. However, prospect theory as initially defined by Kahneman and Tversky (1979) may lead to a violation of in-betweenness —a counterintuitive effect where the certainty equivalent of a lottery is not in between the smallest and the largest possible payoff of the lottery. To avoid this, Tversky and Kahneman (1992) introduced *cumulative prospect theory*, CPT, which applies the probability weighting to the cumulative distribution function in a way Eq. (5.5) becomes

$$w(p) \cdot v(c_1) + 1 - w(p) \cdot v(c_2) \tag{5.6}$$

for binary lotteries. Yet, Rieger and Wang (2008a) observe that not all properties of CPT correspond well with experimental data and that there are some descriptive reasons favoring the original formulation of PT (Hens and Rieger, 2010). In addition, the solution they offer allows to generalize prospect theory to non-discrete outcomes and to make it continuous. Their approach is computationally easier than the corresponding formula for CPT: it simply starts with the original formulation of prospect theory in (5.5), and fixes the violation of in-betweeness problem by simply normalizing the decision weights w(p) so that they add up to 1 and can be interpreted again as a probability distribution (Hens and Bachmann, 2008). The approach goes back to Karmakar (1978) where, for two-outcome prospects, the PT-values are normalized by the sum of the weighted probabilities. Thus, the normalized weights $w^*(p)$ are calculated as

$$w^*(p) = \frac{w(p)}{w(p) + w(1-p)} \tag{5.7}$$

where $w^*(p)$ means normalized weights according to this so-called normalized prospect theory (NPT). NPT has some advantages. Firstly, it cures the violations of state-dominance in lotteries with two outcomes and avoids violations of in-betweenness completely (Hens and Bachmann, 2008). Secondly, it is shown that the normalized PT utility converges to a continuous distribution —Rieger and Wang (2008a) call the resulting model smooth prospect theory (SPT). Thirdly, it is an easier approach to compute that, in particular, simplifies the computation of the loss aversion parameter in our questionnaires, as we will see. Consequently, rather than the cumulative prospect theory —more frequently used in the literature— the normalized prospect theory, NPT, is the approach that we will follow for the purposes of this thesis —see the *scaling* section later on.

We must finally note that, since people's risky choices are stochastic,[156] the core of the PT model is often enhanced by adding a **choice function**: according to Stott (2006), this is often done by positing

[155] The *fourfold pattern* of preferences is one of the core achievements of prospect theory (Kahneman, 2011).

[156] Following Stott (2006), decision-making under risk is stochastic because *"when asked the same question multiple times, people often change their minds"* (p. 104).

a transformation *P(·)* that yields *f(·)*, the likelihood of picking prospect g_1 given an alternative choice g_2.[157] However, we are going to obviate that alternative and use the deterministic NPT in what follows.

Prospect theory, together with overconfidence, will be the basis for the experimental research in Part III. We vindicate our choice based on the evidence that the fourfold pattern of risk-averse and risk-seeking attitudes, diminishing sensitivity and loss aversion have been extensively discussed in the academic literature, related to many market anomalies and managerial performance, and have been related to several other biases. In what follows we provide a short list, just to illustrate. Regarding prospect theory generally speaking, it allows to analyze what Tversky and Kahneman (1992) identify as the *"five major phenomena of choice that violate the standard model (EUT) and set a minimal challenge that must be met by any adequate descriptive theory of choice"* (p.298): namely, framing effects, nonlinear preferences, risk seeking, loss aversion and source dependence. Daniel Kahneman —Amos Tversky died in 1996— was awarded the Nobel Prize in Economic Sciences in 2002 *"for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty"*.[158]

Regarding loss aversion, there is a large empirical literature confirming its presence and relevance in individuals, from calibration tests performed by Fishburn and Kochenberger (1979), Tversky and Kahneman (1992), Schmidt and Traub (2002), Abdellaoui, Bleichrodt and Paraschiv (2007a) and many others, to the literature on the disparities between people's maximum willingness to pay (WTP) and their minimum willingness to accept (WTA) observed by Kahneman, Knetsch and Thaler (1990) *et seq.* The influence of loss aversion may explain many empirical findings. These include the endowment effect (Thaler, 1980), the disposition effect and higher levels of trade when prices are rising than when they are falling (Shefrin and Statman, 1985), the status quo bias (Samuelson and Zeckhauser, 1988), and the equity premium puzzle (Benartzi and Thaler, 1995). Loss aversion has also been able to explain why consumers and managers would take fewer risks (Rabin, 2000), how the number of transactions in the market would be reduced (Knetsch, 1989), narrow framing (Barberis and Huang, 2001), asymmetric price elasticities (Hardie, Johnson and Fader, 1993), and downward-sloping labor supply (Goette, Huffman and Fehr, 2004). Finally, Thaler (1985) provided a model of consumer behavior based on mental accounting and loss aversion. Nonetheless, some limits of loss aversion were also identified (e.g., Novemsky and Kahneman (2005); McGraw et al., 2010), as described in Chapter 4.

The literature on risk seeking is quite extensive, too. Tversky and Kahneman (1992) observe risk-seeking choices in two types of decision problems: a favorite-longshot bias and the aversion to a sure loss —when people prefer a substantial probability of a large loss than a smaller sure loss. Risk seeking is also suggested to explain the house money effect (Thaler and Johnson, 1990) and a biased decision

[157] Formally, $f(g_1 \mid g_2, \theta) = P(V(g_1), V(g_2))$, where θ is a parameter vector.

[158] Source: http://www.nobelprize.org/nobel_prizes/economics/laureates/2002/, the official website of the Nobel Prize.

making in corporate management (Shefrin and Cervellati, 2011). Finally, diminishing sensitivity has been related to several biases and anomalies. Thus, diminishing sensitivity in the weighting function could lead to irrational advice and the making of decisions that contradict the independence axiom (Hens and Bachmann, 2008), what may explain empirical anomalies in financial markets like the IPOs underpricing puzzle (see Chapter 2). In addition, among the biases related to loss aversion we may find the status quo bias (Tversky and Kahneman, 1991) and framing (Tversky and Kahneman, 1986).[159]

5.3. PARAMETRIC SPECIFICATIONS

We concluded in Section 5.2 that, for the purposes of this thesis, we are going to follow the deterministic NPT. Consequently, in what follows we tackle the specification of the value and probability weighting functions within the context of prospect theory.

While the formulation of prospect theory in terms of a kinked utility function and an inverse S-shaped probability weighting function is commonly accepted, a general preference-based method to elicit the utility for gains and losses simultaneously is not available (Abdellaoui et al., 2007). In order to measure loss aversion, utility must be determined completely,[160] but prospect theory assumes people weight probabilities and such weighting may be different for gains than for losses. Consequently, when a parametric functional form is imposed on the value and weighting functions, all parameters must be determined simultaneously. This causes an interpretation problem at best, while things could even go worse if any parameter is misspecified.

Two lines of discussion are relevant here. First, we must decide whether it is better to use parametric or non-parametric measurements. Second, if a parametric method is chosen, which of the many forms suggested for the value and weighting function we use. There are several advantages of non-parametric methods (Abdellaoui et al., 2007; Booij, van Praag and van de Kuilen, 2010). First, when using a parametric method we depend on the appropriateness of the selected functional forms, in the sense that we do not know whether the measures are driven by the data or by the imposed parametric model. Besides, the non-parametric approach provides a direct link between utilities and choices, allowing us to solve inconsistencies in utility measurement. Finally, a major drawback of parameter methods is that they suffer from a *contamination effect*: a misspecification of the utility function will also bias the estimated probability weighting function and vice versa (Abdellaoui, 2000).

[159] Tversky and Kahneman (1986) suggest framing could be influenced by either loss aversion or diminishing sensitivity: a frame that highlights losses of a choice makes that choice less attractive, whereas a frame that makes losses appear small relative to the scales involved exploits diminishing sensitivity, making the choice more attractive.
[160] Meaning utility for gains and for losses must be determined simultaneously.

Notwithstanding, non-parametric measurements also have their flaws. First, they are generally more susceptible to response error. Besides, this approach requires data that have a chained nature which may introduce error propagation leading to less precise inference (Wakker and Deneffe, 1996; Booij et al., 2010). Stott (2006) also finds evidence supporting the use of parametric methods in the context of CPT.[161] But perhaps the major drawback of non-parametric techniques for the purposes of our experimental tests in Part III is that they are less efficient, in the sense that more questions are needed (Abdellaoui, Bleichrodt and L'Haridon, 2008). Since one of our goals in the experiment will be to implement a test that is simple and with a short number of questions, using a parametric approach becomes more desirable to us. This is reinforced by the fact that we want to minimize the possible effects of response errors and misunderstanding by the respondents. Consequently, for the purposes of this thesis we will use a parametric approach. In what follows we determine the specifications of the value and probability weighting functions under a parametric approach.

5.3.1. The value function

As mentioned above, in prospect theory the utility function is substituted by a value function that is defined over changes in wealth rather than over the final wealth, satisfying three important properties: reference dependence, diminishing sensitivity and loss aversion. That results in a value function that (1) it is defined over gains and losses with respect to some reference point; (2) it is concave in gains and convex for losses; (3) the function is steeper for losses than for gains. There are several parametric specifications that satisfy those properties. For instance, the (piecewise) power function by Tversky and Kahneman (1992)

$$v(x) = \begin{cases} x^{\alpha+} & for\, x \geq 0 \\ -\beta(-x)^{\alpha-} & for\, x < 0 \end{cases} \tag{5.8}$$

—where x accounts for gains (if $x \geq 0$) or losses (if $x \leq 0$), α^{+} measures sensitivity to gains, α^{-} does the same to losses, and β measures loss aversion— is the most widely used parametric family to represent the value function because of its simplicity and its good fit to experimental data (Wakker, 2008). Also known as the family of constant relative risk aversion (CRRA),[162] the power function is used to fit the curvature of the value function for gains since it helps modeling risk aversion. Measurements of the shape of utility have generally confirmed PT's assumptions of concave utility for gains and convex utility

[161] According to Stott (2006), *"the contention that non-parametric models are somehow preferable has been tempered. Whilst this parametric freedom may be necessary where the shape of the function is itself under investigation, this reasoning does not apply to other situations. In these cases it is explanatory power that counts. The current results show that parametric forms of CPT generally fit risky decision-making data better than non-parametric ones"* (p.123). However, whenever some shape property is under investigation, the non-parametric form represents the only unbiased way of conducting a descriptive investigation.

[162] Booij et al. (2010) notice the power function could be referred to as CRRA only under EUT; under non-expected utility models such as prospect theory, this designation is no longer appropriate, because whether an agent is willing to pay a constant fraction of wealth to avoid risking a fair gamble over percentages of wealth depends as well on probability weights, whether the reference point changes over time, etc.

for losses, both at the aggregate and the individual level, with estimated power coefficients between 0,70 and 0,90 for gains (α^{+}) and between 0,85 and 0,95 for losses (α^{-}) —Abdellaoui et al. (2008).[163]

Less frequently used parametric specifications —see Table 5.1 below— are the exponential and expo-power utility functions[164] and the quadratic function (Hens and Bachmann, 2008), which has played a prominent role in Finance.[165] Stott (2006) tests eight value functions in combination with eight probability weighting functions and four choice functions; the value functions include power, exponential and quadratic, as well as linear (representing risk neutrality), logarithmic, a linear-plus-exponential (labeled *Bell* after Bell and Fishburn, 2000), a HARA function (hyperbolic absolute risk aversion) and a non-parametric form. This combinatorial approach has the merit of trying to disentangle the above mentioned contamination effect of parametric measurements by testing each value function specification in conjunction with all the other possible configurations of weighting and choice functions. Stott's results support the power function form when combined with Prelec-I weighting function and Logit stochastic choice function.

TABLE 5.1 – Value and weighting functions in the literature

VALUE FUNCTION		
Power	$v(x)=\begin{cases} x^{\alpha+} & for\ x\geq 0 \\ -\beta(-x)^{\alpha-} & for\ x<0 \end{cases}$	Tversky & Kahneman (1992)
Exponential	$v(x) = 1 - e^{-\alpha x}$ for $\alpha > 0$	Abdellaoui et al. (2007b)
Expo - power	$v(x) = exp(-z^{\alpha}/\alpha)$ for $\alpha \neq 0$	
Quadratic	$v(x)=\begin{cases} x-\frac{\alpha^{+}}{2}\cdot x^{2} & if\ \frac{1}{\alpha^{+}}>x\geq 0 \\ \beta(x-\frac{\alpha^{-}}{2}\cdot x^{2}) & if\ \frac{1}{\alpha^{-}}<x<0 \end{cases}$	Hens & Bachmann (2008)
Linear	$v(x) = x$	Stott (2006)
Logarithmic	$v(x) = ln\ (a + x)$	
Bell	$v(x) = b\cdot x - e^{-\alpha x}$	
HARA	$v(x) = -(b + x)^{\alpha}$	

WEIGHTING FUNCTION			
one parameter	**Linear**	$w(p) = p$	Stott (2006)
	Power	$w(p) = p^{\alpha}$	
	T&K'92	$w(p)=\frac{p^{\gamma}}{\left(p^{\gamma}+(1-p)^{\gamma}\right)^{1/\gamma}}$	Tversky & Kahneman (1992)
	Prelec-I	$w(p)=\exp(-(-\log(p))^{\gamma})$	Prelec (1998)
two param	**Prelec-II**	$w(p)=\exp(-\delta(-\log(p))^{\gamma})$	
	W&G'96	$w(p)=\frac{p^{\gamma}}{\left(p^{\gamma}+(1-p)^{\gamma}\right)^{\delta}}$	Wu & Gonzalez (1996)
	G&E'87	$w(p)=\frac{\delta\cdot p^{\gamma}}{\delta\cdot p^{\gamma}+(1-p)^{\gamma}}$	Goldstein & Einhorn (1987)

Source: Own elaboration, based on authors named in the Table

[163] Since Tversky and Kahneman (1992) obtained the same median estimation for the exponent ($\alpha^{+} = \alpha^{-} = 0.88$), in their first estimation, some authors have used a single α parameter for simplification purposes —see for instance Hens and Bachmann (2008). However, most empirical research support differences are significant, with concave utility for gains while for losses the evidence is mixed, and closer to linearity than for gains anyway (Abdellaoui et al. 2008; Booij et al. 2010).
[164] For further info, their properties are described in Abdellaoui, Barrios and Wakker, 2007b.
[165] A reason for this is that the quadratic utility is associated with the traditional measurement of risk. Stott (2006) explains that one property of the quadratic transformation is that its evaluation of a prospect can be restated in terms of the prospect's statistical mean and variance. Hens and Bachmann (2008) explain that this parametric specification allows to make the choice of the behavioral investor compatible with the mean-variance framework for any return distribution. It is worth noting the poor performance of this function according to the results by Stott, who claims it would question the descriptive accuracy of mean-variance portfolio analysis —variance does not seem to capture people's risk aversion as well as other risk measures.

Finally, we should note that the second property required to any value function —namely, that the function is concave for gains and convex for losses, reflecting the principle of diminishing sensitivity— applies to the weighting function as well. This way, in the context of the value function, diminishing sensitivity implies that both $\alpha^+ < 1$ and $\alpha^- < 1$ (Booij et al., 2010), such that the marginal effects in perceived well-being are greater for changes close to one's reference level than for changes further away (Rabin, 1998). However, in prospect theory risk aversion and risk seeking must be determined jointly by the value and weighting functions.

5.3.2. The probability weighting function

As mentioned, in prospect theory the objective probabilities are replaced by subjective decision weights. Decision makers usually do not treat probabilities linearly, but overweight rare events and underweight events with a higher probability. Psychologically, the mathematical step from zero to a one percent probability is a huge step since it turns an impossible event into a possible one, and this is surely a larger psychological step than a change from 49% probability to 50% probability (Hens and Bachmann, 2008). Under prospect theory, people evaluate risk using *transformed* rather than objective probabilities, where transformed probabilities are obtained by applying a weighting function to the objective probabilities. The main effect of this transformation is the overweighting of the tails of the distribution it is applied to, an overweighting that does not represent a bias in beliefs: *"it is simply a modeling device that captures the common preference for a lottery-like, or positively skewed, wealth distribution"* (Barberis and Huang, 2008, p. 2066).

Tversky and Kahneman suggest those weights may be calculated using a probability weighting function, denoted $w(p)$, where low probabilities (close to both 0 and 1) are over-weighted. This would help to explain the classic financial puzzle of why a given person may simultaneously demand lottery and insurance: most people prefer ($5,000, 0.001) over a certain $5, and most also prefer a certain loss of $5 over (-$5,000; 0.001). There are several parametric functions that have been suggested that meet the required properties of a weighting function. The alternatives are basically two-parameter vs. one-parameter functional forms. One-parameter specifications are a classic in the literature since Tversky and Kahneman (1992) suggested the form

$$w(p) = \frac{p^\gamma}{\left(p^\gamma + (1-p)^\gamma\right)^{1/\gamma}} \tag{5.9}$$

where p is the objective probability and γ measures the curvature of the function. Again, two different gamma parameters could be used (γ^+ and γ^-) —whether we want to measure different weighting functions for gains and for losses— or just a single one. Tversky and Kahneman noted this form has some advantages: it has only one parameter (meaning it is easier to estimate), it encompasses an inverted S-shaped weighting functions with both concave and convex regions and, most important, it provides a reasonably good approximation to both aggregate and individual data. Notwithstanding, other authors suggest alternative one-parameter functional forms —see Table 5.1— including Wu and Gonzalez (1996), the linear and power functions (Stott, 2006) and the Prelec-I function (Prelec, 1998).

However, some authors (e.g., Goldstein and Eihorn, 1987; Prelec, 1998) provide two-parameter specifications that are able to explain two distinct properties that can be given a psychological interpretation (Gonzalez and Wu, 1999; Booij et al., 2010). One parameter measures the degree of *curvature* of the weighting function, while the other would measure its *elevation*. The psychological interpretation would be, on one hand, that the curvature would measure how the decision maker discriminates probabilities —a property labeled *discriminability*, closely related to the notion of diminishing sensitivity, where the probability of 0 (impossibility) and 1 (certainty) serve as reference points. On the other hand, the elevation of the weighting function might be interpreted as how attractive the decision maker views gambling —a property labeled *attractiveness*.

Two classic versions of the one-parameter and two-parameter functional forms were provided by Prelec (1998), where the single parameter version, denoted Prelec-I,

$$w(p) = \exp(-(-\log(p))^{\gamma}) \ , \tag{5.10}$$

would be a particular case of the two-parameter form, denoted Prelec-II,

$$w(p) = \exp(-\delta(-\log(p))^{\gamma}) \ , \tag{5.11}$$

when δ = 1. Though Booij et al. (2010) note one-parameter forms cannot set curvature and elevation independently —hence their estimates will lead to biased inferences if curvature and elevation do not co-vary accordingly— Stott (2006) finds the two-parameter functional forms are less attractive than the one-parameter versions. In particular, Stott finds Prelec-I would be preferred to Prelec-II, as well as to any other alternatives we may use when combined with the power value function. Consequently, for the purposes of this thesis, we will set the Prelec-I form as the specification-by-default for the weighting function, with decision weights $w(p)$ being subsequently normalized to $w^*(p)$ following normalized prospect theory (NPT).

5.3.3. Set of variables and attitudes towards risk

To sum up, in subsections 5.3.1 and 5.3.2 we decided to use a parametric approach in the experimental research we will conduct in Part III, with the power value function —Eq. (5.8)— and the Prelec-I weighting function —Eq. (5.10)— as options by default. Therefore, we have five parameters (α^+, γ^+, α^-, γ^- and β) that we must estimate. These will be the **factors** in the experimental research related to prospect theory —the other three are related to overconfidence, as we will see—, namely:

- Risk aversion (α^+) over gains, which measures the concavity of the value function for gains.

- Risk aversion (α^-) over losses, a.k.a. aversion to a sure loss, measuring risk seeking (convexity of the value function for losses): *"Just as the concavity of the value of gains entails risk aversion, the convexity of the value of losses entails risk seeking"* (Kahneman and Tversky, 1984, p. 342).
- Loss aversion (β), measuring how steeper the value function is for losses than for gains —i.e., people suffer a loss more acutely than enjoy a gain of the same magnitude (Shefrin, 2006).
- Probability weights (γ^+ for gains, γ^- for losses), which determine the probability weighting function —that is, how people distort given probabilities.

How the five factors are measured, calibrated and interpreted will be explained in Section 5.4. What is relevant here is to note that, though these five parameters synthetize the *diminishing sensitivity* and *loss aversion* properties in PT, when it comes to provide an interpretation to three different attitudes towards risk (risk aversion and risk seeking in the fourfold pattern of preferences, plus loss aversion), things are not that simple. In prospect theory we must be careful about the interpretation of the results we are to obtain, for two particular reasons. One is the more complex interpretation of concepts like risk aversion and risk seeking, concavity and convexity, under prospect theory. The other is in regard to debate about the definition of loss aversion and how to measure it, which represents one of the main challenges for prospect theory nowadays. In this subsection we deal with the first topic, while the problem with loss aversion is analyzed in subsection 5.3.4.

Most empirical studies have confirmed the positive validity of the probability weighting function (Tversky and Kahneman, 1992; Camerer and Ho, 1994; Wu and Gonzalez, 1996; Gonzalez and Wu, 1999) and the concavity of the utility function for gains (Abdellaoui, 2000; Abdellaoui, Vossmann and Weber, 2005). The evidence on the utility for losses is however less clear-cut (Abdellaoui et al., 2007). Most studies support the theoretical assumption of a convex utility for losses (e.g., Fishburn and Kochenberger, 1979), but concave and linear utilities are also observed (Abdellaoui et al., 2007). This would lead a naive reader to interpret that a risk averse behavior in the domain of losses is quite regular, but not so. Straightforward concepts in expected utility theory like risk aversion or risk seeking are tough to disentangle under prospect theory. Under EUT, the convexity of the utility function is equivalent to risk seeking; under PT, however, this equivalence no longer holds. For instance, Chateauneuf and Cohen (1994) prove a subject with a convex utility function can be risk averse if he is 'sufficiently pessimistic', and vice versa. *"For example, if a subject indicates that he is indifferent between a sure loss of €40 and the two-outcome prospect (-€100, 1/2; €0), then (...) this risk-seeking preference is consistent with a concave utility for money if $w^-(1/2) < 0,4$"* (Abdellaoui et al., 2007, p.1661).

Consequently, we must be aware that the fourfold pattern of preferences implies that risk aversion and risk seeking depend on, at least,[166] two parameters. On one hand, subjects exhibit the higher risk aversion the lower both α^+ and γ^+ coefficients for gains of moderate/high probability, and the lower γ^- for losses of low probability. On the other hand, subjects are the more risk seeking the lower both α^- and γ^- coefficients for losses of moderate/high probability, and the lower γ^+ for gains of low probability. This is far more complex than capturing the risk-taking tendency only through the concavity of the utility function. Following Hens and Bachmann (2008), *"prospect theory implies that risk-taking behavior is conjointly determined by (1) how people choose the reference point, (2) risk attitudes in gains and losses, (3) the degree of loss aversion, and (4) how people judge and weight probabilities. This is far more complicated than the standard expected utility theory which captures the risk-taking tendency only through the concavity of the utility function"* (p.98). Hence, this is how the different attitudes towards risk should be interpreted under PT:

i. **Risk aversion**. Subjects tend to be risk averse (1) for gains of moderate/high probability, and (2) for losses of low probability. (1) is measured with the coefficients α^+ and γ^+: the lower both α^+ and γ^+ coefficients, the higher risk aversion; (2) is measured with γ^- coefficient: the lower γ^-, the higher risk aversion.

ii. **Risk seeking**. Subjects tend to be risk seeking (3) for losses of moderate/high probability, and (4) for gains of low probability. (3) is measured with the coefficients α^- and γ^-: the lower both α^- and γ^- coefficients, the higher risk seeking; (4) is measured with γ^+ coefficient: the lower γ^+, the higher risk seeking.

iii. **Loss aversion**. It measures the asymmetry between gains and losses that is far too extreme to be explained by income effects or by decreasing risk aversion (Kahneman and Tversky, 1984). It is measured through the β coefficient: the higher the β, the higher the loss aversion.

Kahneman (2011) summarizes the above in two basic hypotheses he considers to be the essence of prospect theory. First, in bad choices, where a sure loss is compared to a larger loss that is merely probable, diminishing sensitivity causes risk seeking. Second, in mixed gambles, where both a gain and a loss are possible, loss aversion causes extremely risk averse choices.

5.3.4. The problem with loss aversion

In mixed gambles, where both a gain and a loss are possible, prospect theory predicts that loss aversion —the pronounced asymmetry of the value function— causes extremely risk averse choices (Kahneman, 2011). As we saw in Section 5.2, there is an extensive empirical literature confirming the presence and relevance of loss aversion for most individuals. However important loss aversion is recognized, a major

[166] We say at least because for two-parameter weighting functions the effect of δ^+ and δ^- parameters measuring the attractiveness of gambling should be considered, too.

challenge in the literature on prospect theory is that neither a generally accepted definition of loss aversion, nor an agreed-on way to measure it is available.

Tversky and Kahneman (1992) defined loss aversion implicitly as $\beta = -\frac{u(-1)}{u(1)}$, which might be seen as an approximation of the definition proposed by Köbberling and Wakker (2005), who characterized loss aversion as the ratio between the left and right derivatives of the utility function at zero, i.e., $\beta = \frac{U_{\uparrow}^{'}(0)}{U_{\downarrow}^{'}(0)}$, where $U_{\uparrow}^{'}(0)$ denotes the left and $U_{\downarrow}^{'}(0)$ the right derivative of the utility function at 0. Köbberling and Wakker show that the CRRA family of functions (i.e., log-power) encounter difficulties when modeling loss aversion: the power function amounts to the implicit scaling convention that $u(1) = -u(-1) = 1$, what implies the formula for loss aversion by Tversky and Kahneman (1992) above mentioned. However, this scaling convention depends on the unit of payment[167] which means that, at best, loss aversion can only be defined relative to the unit of money chosen. Thus, only when the curvature parameters in the power function (i.e., α^{+} and α^{-} in our notation) are the same can loss aversion be a dimensionless quantity.[168]

Other interpretations of loss aversion available are those by Kahneman and Tversky (1979), Wakker and Tversky (1993), Bowman, Minehart and Rabin (1999) and Neilson (2002). Kahneman and Tversky originally defined loss aversion as $-u(-x) > u(x)$ for all $x > 0$, Wakker and Tversky made a stronger version given by $u'(-x) \geq u'(x)$ for all $x > 0$, while Bowman et al. made it stronger by suggesting loss aversion holds if $u'(-x) \geq u'(y)$ for all positive x and y.[169] Finally, Neilson (2002) proposed to define loss aversion as $u(-x)/x \geq u(y)/y$ for all positive x and y. However, none of these definitions provide a straight index of loss aversion, but formulate it as a property of the utility function over a whole range (Booij et al., 2010).

Some authors have provided some alternative solutions to elicit loss aversion (e.g., Abdellaoui et al. 2008; Booij et al. 2010), but the debate is still open. In consequence, we opt for a solution that is inspired by Booij et al. (2010) —by picking up *"all the questions around the zero outcome"* (p.130)— and by empirical finding that utility is close to linear for moderate amounts of money (Rabin, 2000). First, questions in the experimental test designed to elicit loss aversion will ask for small amounts of money. Second, we will ask participants in our experiment for a few prospects with small amounts of money

[167] This means for example that exactly the same data, expressed in dollars on one hand, or alternatively expressed in cents on the other, yields different measures of loss aversion (see Wakker, 2010).
[168] Köbberling and Wakker (2005) show constant absolute risk averse (CARA, i.e., linear-exponential) utility functions performs better in this regard, hence they propose as a solution a CARA utility function that does not have extreme derivatives at 0 —as it happens with power functions whenever the power is not 1. However, the prevailing empirical finding is increasing relative risk aversion and decreasing absolute risk aversion (Arrow, 1971), which is between CRRA and CARA (Abdellaoui et al., 2007b).
[169] Note Wakker and Tversky (1993) definition implies the slope of the utility function at each loss is at least as large as the slope of the utility function at the absolutely commensurate gain; Bowman et al. (1999), instead, suggest the slope is everywhere steeper than the slope of the utility function for gains (Abdellaoui et al., 2007).

and assume $\alpha^+ = \alpha^- = 1$ to estimate β (as a mean or median). This solution will be explained more in detail in the next section. Nonetheless, we must be aware that ours is an arbitrary choice and serves only as an imperfect solution to a more complex problem, suggesting we have to be careful when comparing loss aversion estimates. In addition, Por and Budescu (2013) discuss some violations of the gain-loss separability which may limit the generalization of results from studies of single-domain prospects to mixed prospects.

5.4. ELICITATION METHODS AND SCALING

The purpose of this section is to determine how we will elicit the parameters in the value and weighting functions of a respondent, given we assume a piecewise power value function as in Eq. (5.8) and the Prelec-I weighting function —Eq. (5.10)— as parametric functional forms under normalized prospect theory, NPT. Various elicitation procedures have been proposed for this purpose. The most common methods to elicit utility under EUT are the certainty-equivalent, the probability-equivalent, direct scaling and the lottery-equivalent methods (Wakker and Deneffe, 1996).[170] In the context of PT, perhaps the most common is the elicitation of *certainty equivalents* (indeed it is the one Tversky and Kahneman (1992) used): we seek to obtain the cash equivalents to a series of prospects by asking the respondents a series of refined choice questions, then estimating the value and weighting functions using nonlinear regression, assuming a specific parametric functional form for each one (Wu and Gonzalez, 1996).

In the design of the questionnaires in the experiment we follow Abdellaoui et al. (2008). In particular, the elicitation method requires three sets of questions. The first set involves only two-outcome, positive prospects (i.e., a gamble where the respondent may win some positive quantity or zero, for instance "95% chance to win 1.000€ and 5% chance to win 0€") devised to calibrate for each respondent the parameters α^+ and γ^+ of the value and probability weighting functions in the positive domain. The second set of questions involves only two-outcome, negative prospects (i.e., the respondent may lose some money or zero otherwise), designed to calibrate α^- and γ^- parameters in the negative domain. Finally, the utility of gains and losses are linked through a third set of questions, regarding the acceptability of mixed prospects (e.g., 50% chance to lose 100€ and 50% chance to win *x*), with the aim to measure loss aversion —the β parameter in the value function.

In the first set, for each prospect of the form (x, p; 0, 1-p) respondents are required to provide their certainty equivalent, c. That is, the sure payoff they should be given as to be indifferent between

[170] Other methods include the trade-off method, introduced by Wakker and Deneffe (1996), which is robust to probability weighting when all outcomes are of the same sign, and the four-step method proposed by Abdellaoui et al. (2007), primarily based on the elicitation of certainty equivalents for utility midpoints (i.e., decision weights of 0.5).

gambling and being paid. Similarly, in the second set respondents are required to provide c, though now prospects are negative and consequently the alternative quantity is the sure loss the respondent should pay that makes her indifferent between gambling and paying. Denote c/x the ratio of the certainty equivalent of the prospect —derived from observed choices by the respondent— to the nonzero outcome x. Plotting c/x as a function of p —one function for positive and another for negative prospects— we obtain two smooth curves, interpreted as weighting functions assuming a linear value function.

The calibration of parameters in the value and weighting functions require, henceforth, to be calibrated jointly using a nonlinear regression procedure separately for each subject. By definition, for each question the expected utility of the prospect should be equal to the utility of the certainty equivalent. Under NPT this makes

$$V(c) = w^*(p)\cdot V(x) + (1-w^*(p))\cdot V(0) = w^*(p)\cdot V(x) \ , \tag{5.12}$$

since all questions in the questionnaire are two-outcome prospects. We may solve equation (5.12) using the power function in (5.8) to have

$$c^\alpha = w^*(p)\cdot x^\alpha \ \rightarrow \ c/x = \left[w^*(p)\right]^{1/\alpha} \ , \tag{5.13}$$

for the positive domain, whereas for losses we get a similar result

$$-\beta\cdot(-c)^\alpha = -\beta\cdot(-x)^\alpha\cdot w^*(p) \ \rightarrow \ -\frac{c}{x} = \left[w^*(p)\right]^{1/\alpha} \ . \tag{5.14}$$

Thus, the certainty equivalents provided by the respondent in the first set allow us to calibrate α^+ and γ^+ for gains, while those in the second set allow us to do the same for α^- and γ^- in the negative domain. Once we have calibrated α^+ and γ^+ for gains, as well as α^- and γ^- for losses, we check: (1) whether they are significantly below one —meaning utility function is concave for gains and convex for losses— and (2) whether they are significantly different from each other —that is, whether $\alpha = \alpha^+ = \alpha^-$ and $\gamma = \gamma^+ = \gamma^-$.

Finally we have to calculate β, the loss aversion parameter. In order to solve for it we have to compare mixed prospects, as to identify the different behavior of the respondent in the positive versus negative domain. Consequently, questions in the third set ask a classic in the literature (e.g. Hens and Bachmann, 2008, p. 120): *"someone offers you a bet on the toss of a coin. If you lose, you lose €X. What is the minimal gain that would make this gamble acceptable?"*, where X is a moderate amount of money (1 to 100 euros, for instance). This way, all questions to calibrate loss aversion set probabilities of success and failure equal to 50%, p = 0.5. Consequently, since $w^*(0.5) = 0.5$ under NPT, the answer provided by the respondent makes the utility of a gain (V^+) equivalent to the disutility of a loss (V^-).[171] For example, for the piecewise power utility function we have

$$0{,}5 \cdot V^{+}(G) = -0{,}5 \cdot V^{-}(L) \;\rightarrow\; G^{\alpha+} = \beta \cdot (-L)^{\alpha-} \;\rightarrow\; \beta = \frac{G^{\alpha+}}{(-L)^{\alpha-}}\,, \qquad (5.15)$$

where G means gains, L losses, and loss aversion would be equal to the ratio $G/|L|$ only in the particular case where $\alpha = \alpha^{+} = \alpha^{-}$. That would be indeed the only particular case where β is not affected by changes of scale regarding units of payment (Köbberling and Wakker, 2005) and hence it would be well-defined, as discussed in subsection 5.3.4.

5.5. OVERCONFIDENCE IN THE LITERATURE

The prevalence of overconfidence, i.e., the human tendency to overestimate our own skills and predictions for success (Ricciardi and Simon, 2000), is a classic in the behavioral finance. For instance, De Bondt and Thaler (1995) consider it the more robust finding in the psychology of judgment, while Plous (1993) asserts *"no problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence"* (p. 217). Hence, we vindicate our choice for overconfidence based on the fact that overconfidence has been extensively discussed in the academic literature, related to many market anomalies and managerial performance, and has been related to several other biases. In what follows we provide a short list, just to illustrate.

5.5.1. The prevalence of overconfidence

Most academic reviews include overconfidence as one of the most relevant heuristic-driven biases, including Kahneman, Slovic and Tversky (1982), Shiller (2000a), Shefrin (2000), Barberis and Thaler (2003) and Hens and Bachmann (2008). Early literature may be traced back to the 1960s, like Oskamp (1965) and Alpert and Raifa (1969). Overconfidence has been suggested to be a consequence of several other biases, such as confirmation bias (Koriat, Lichtenstein and Fischhoff, 1980), hindsight bias (Fischhoff, 1982b), illusion of control (Barber and Odean, 2002) and self-attribution bias (Statman, Thorley and Vorkink, 2006). Besides, Keren (1987) and Griffin and Tversky (1992) suggest *ambiguity* of evidence is a relevant mediating factor in both overconfidence and confirmation bias. Research showing people tend to consider themselves above average includes, among many others, Fischhoff, Slovic and Lichtenstein (1977), Svenson (1981), Dunning, Meyerowitz and Holzberg (1989), Dunning, Heath and Suls (2004) and Williams and Gilovich (2008).

[171] This is indeed one advantage, for the sake of simplicity, NPT introduces in the elicitation of the parameters in prospect theory: the elicitation of the parameter β for loss aversion becomes more tractable.

Experimental research has confirmed the role of overconfidence in areas as diverse as health, driving, insurance markets, job search (see review by Sandroni and Squintani, 2009) and consumer behavior —e.g., the classic 'paying not to go to the gym' by DellaVigna and Malmendier (2006). Within financial markets, Biais et al. (2005) show overconfident traders experience poorer trading performance in an experimental setting. Experimental evidence also shows men tend to be more overconfident (Lundeberg, Fox and Punccohar, 1994) —with gender differences being highly task dependent—,[172] trade more frequently and exhibit more losses than women (Barber and Odean, 2001). Finally, Chen et al. (2007) also appreciated cultural differences, with Chinese investors appearing to be more overconfident than American.

Many anomalies in financial markets are suggested to be a result from investors' overconfidence. Investors are likely overstate their risk tolerance (Hirshleifer, 2001; Barberis and Thaler, 2003) fostering market anomalies such as excess volatility and return predictability (Daniel, Hirshleifer and Subrahmanyam, 1998), excessive trading (Kyle and Wang, 1997; Odean, 1998b, 1999; Hong, Scheinkman and Xiong, 2006; Grinblatt and Keloharju, 2009), the forward premium puzzle (Burnside et al., 2011), sensation seeking (Grinblatt and Keloharju, 2009), under-diversification (Goetzmann and Kumar, 2008), the favorite long-shot bias (Hens and Bachmann, 2008), and many others. Consequently, several authors have provided models based on investor overconfidence that explain the generation of asset bubbles (Scheinkman and Xiong, 2003) the wrong assessment of risk in insurance markets (Sandroni and Squintani, 2007), or how overconfident traders appear in a multi-period market when they can learn about their ability (Gervais and Odean, 2001).

Finally, research is vast regarding managerial overconfidence —indeed, executives appear to be particularly prone to display overconfidence (Moore, 1977).[173] This includes Roll, 1986 (corporate takeovers), Camerer and Lovallo, 1999 (high rates of business failure), Heaton, 2002 (underinvesting if having to seek external funds), Malmendier and Tate, 2005a,b (high rates of M&A), Liu and Taffler, 2008 (M&As), Malmendier and Tate, 2008 (corporate diversification), Deshmukh, Goel and Howe, 2010 (lower dividend payout), Malmendier, Tate and Yan, 2011 (acquisitions), Huang, Lambertides and Steeley, 2012 (higher cash holdings), and Andreou, Doukas and Louca, 2012 (corporate diversification). A common signal of overconfidence among CEOs is that they tend not to exercise their stock-options early, given a sufficiently high stock price, as they should do (Hall and Murphy, 2000, 2002).

5.5.2. Overconfidence vs Thurstonian and Brunswikian theories

A branch of the behavioral finance suggests it is heuristics and cognitive biases what causes the overconfidence phenomenon. However, there are alternative views. Two relevant ones are the

[172] Meaning men feel even more overconfident in tasks that are perceived to be 'masculine'.

[173] Three factors would trigger overconfidence: the illusion of control, a high degree of commitment to good outcomes, and abstract reference points that make performance comparisons complex (Alicke et al., 1995; Malmendier and Tate, 2005a,b).

ecological and error models. Brunswikian or ecological models suggest overconfidence would be a result from a biased, even tricky, selection of items by researchers. According to this view, people are good judges of the reliability of their knowledge as long as such knowledge is representatively sampled from a specified reference class (Gigerenzer, Hoffrage and Kleinbölting, 1991). For example, overconfidence in tests of general knowledge might be a consequence of the procedures involved in the creation of traditional general knowledge items when they are "informally selected by human selectors instructed to select items that differentiate between more and less knowledgeable subjects", rather than as the result of a cognitive bias (Juslin, 1994). When objects in the almanac items are selected randomly from a natural environment, people are well-calibrated and overconfidence disappears. Dawes and Mulford (1996) suggest a similar interpretation. Gigerenzer et al. (1991) also specified the conditions under which overconfidence and the hard-easy effect[174] can be made to appear, disappear, and even invert. The name given to these theorists comes from the probabilistic functionalism of Brunswik (1952) that influenced these ecological models (Ayton and McClelland, 1997).

Thurstonian or error models, on the other hand, start with the regression effects in the tradition of Thurstone (1927) noted by Erev, Wallsten and Budescu (1994): both over and underconfidence may be obtained from the same data set depending upon whether accuracy is conditioned on confidence or vice versa. This simultaneous feature of over and underconfidence can be attributed to the existence of a random error in well-calibrated probability judgments coupled with the method of analysis (Ayton and McClelland, 1997). Thus, because of the correlation between subjective and objective probabilities, when objective probabilities are plotted against subjective, the regression will most often contribute to overconfidence (Juslin, Winman and Olsson, 2000). Overconfidence would be merely an illusion, created by unrecognized regression.

The ecological argument was dismissed by some authors claiming that the representative item selection was confounded with the hard-easy effect. Thus, Brenner et al. (1996) argue overconfidence cannot be explained as a selection bias and it is not eliminated by a random sampling of questions. Furthermore, Suantak, Belger and Ferrell (1996) provide experimental evidence that the biased choice of stimulus argument is not correct, concluding the most likely explanation of the hard–easy effect is in terms of response criteria. However, Juslin et al. (2000) claim there is very little support for a cognitive bias behind the hard-easy effect, which might indeed be near eliminated when there is control for scale-end effects and linear dependency.[175]

[174] Several authors highlighted situations where underconfidence was prevalent on easy tasks (for a list of references see Moore and Healy, 2008). This contradicted the mainstream view that overconfidence was prevalent. As we will describe in Section 5.6., identifying the three different measures of overconfidence by Moore and Healy (2008) was determinant for the authors to propose a theory of overconfidence that could explain the hard-easy effect: on easy tasks, people tend to underestimate their performance but overplace themselves compared to others; hard tasks, instead, produce overestimation and underplacement.

[175] Scale-end effects refer to the fact that overconfidence scores —defined as the difference between the mean subjective probability assigned to the chosen answer and the proportion of correct answers— is mathematically constrained: when the proportion of correct answers is 50% or less, the score can only be zero or positive (overconfidence), reaching its maximum

Some authors proposed a sort of integrative theories of Thurstonian and Brunswikian models. Soll (1996) models reported confidence as a function of the validity of information and a random error. He predicts greater overconfidence for question sets where informational cues are less valid (the hard-easy effect) and that unrepresentative design (ecological models) is a sufficient but not necessary condition for overconfidence. Dougherty (2001) describes a 'multiple-trace memory model' that integrates the ecological and error models and predicts overconfidence should decrease both with experience and improved encoding quality.

Moore and Healy (2008) find these integrative theories useful since they show how the two perspectives are consistent with one another. However, these theories explain results from an item-confidence paradigm, while Moore and Healy suggest perceptions of performance must be measured over a set of items. In addition, they consider their theory of overconfidence (see Section 5.6 next) consistent with a Thurstonian explanation for the hard-easy effect,[176] but claim the random error in human judgment is not sufficient to produce systematically biased estimates. They cite empirical results (Moore and Small, 2008) that show the hard-easy effect persists even for tasks on which neither performance nor its measurement is bounded by floors or ceilings. Besides, they argue, Thurstonian theories are not able to explain overplacement, while their theory does.

The debate continues today. Klayman et al. (1999) offer three experiments devised to separate psychological biases from statistically inevitable effects, and find an overconfidence bias particularly with subjective confidence intervals. Dunning et al. (2003) suggest poor performers are doubly cursed: if they lack the skills to produce correct answers, they are also cursed with an inability to know when their answers are right or wrong. Incompetence would lead poor performers to overconfidence. In addition, top performers would be miss-calibrated, too: they tend to have a good sense of how well they perform in absolute terms, but overestimate how well other people do —they show underplacement. Benoit and Dubra (2011) argue the overplacement on simple tasks and underplacement on difficult ones in the hard-easy effect is consistent with rational Bayesian updaters.

Contrariwise, Merkle and Weber (2011) find people show considerable overplacement as a consequence of a psychological bias that is inconsistent with rational information processing. Stankov et al. (2012) suggest that a more complex account of the miss-calibration effect is needed to incorporate both task characteristics and individual differences. Furthermore, Fellner and Krüger (2012) claim a discrepancy between models and measures of overconfidence exists. Finally, Merkle (2009) finds all types of judges exhibit the hard-easy effect in almost all realistic situations. Hence, he argues the effect

---

when the mean subjective probability is 100% (vice versa when the proportion of corrects is 100%). Because at the ends of the probability scale errors have only one way to go, response errors combined with the salient endpoints of the probability scale will produce a hard-easy effect. Linear dependency, on the other hand, refers to the fact that the proportion of correct answers, c, and the over/underconfidence score, $x - c$, are linearly dependent, which might contribute to the hard-easy effect.

[176] Their theory lies on the assumption that people make imperfect estimates of their own performances and predicts those who perform worst are more likely to overestimate their performances.

cannot help us distinguish between judges or to draw support for neither of the alternative explanations of its existence.

5.6. A THEORY OF OVERCONFIDENCE

When we delve a little into the concept of overconfidence, we find things are even more complex than we have already seen. Moore and Healy (2008) claim the bias had been studied in inconsistent ways. In particular, they identify three different measures of overconfidence that have been confounded in the literature before. Thus, following their approach, people may exhibit overconfidence: (1) in estimating their own performance (known as *overestimation*); (2) in estimating their own performance relative to others (known as *overplacement* or better-than-average effect); and (3) having an excessive precision to estimate future uncertainty (known as *overprecision*). The taxonomy helps Moore and Healy identify the three most notable ways overconfidence has been inconsistently studied in previous research: namely, confounding overestimation and overprecision, some evidence of underconfidence, and the inconsistency between overestimation and overplacement. Then, they provide then a model that represents the core of their work. People have imperfect information about their own performances, but even worse information about the performances of others. As a result, their post-task estimates of themselves are regressive, but their estimates of others are even more regressive. Thus, when people perform better (worse) than they expected, they under (over) estimate their results on average and over (under) place their performance relative to others. The main predictions are that overestimation increases with task difficulty but overplacement decreases with task difficulty, while overprecision would be a more systematic result.

In the experimental research in Part III we will follow Moore and Healy (2008) for several reasons. First, the clarification of the three different ways the literature had studied overconfidence has been widely accepted since then. Second, they were able to make a synthesis of the previous debate between ecological and error models versus the cognitive bias interpretation,[177] offering a model that applies the Bayesian principle of updating from prior beliefs based on data. Third, their model is able to predict both overconfidence and underconfidence in two of its different manifestations (estimation and placement) as well as the hard-easy effect. Finally, their tests are really simple, allowing us to implement a highly efficient test that requires only a few minutes to perform it.

Moore and Healy's model makes richer predictions about people's overconfident behavior. People could either over or underestimate their performance, over or underplace them compared to others,

[177] They implement frequency judgments since there is consensus that they are less prone to overconfidence, and suggest their theory is quite consistent with the Thurstonian view of the hard-easy effect —though not being a straight Thurstonian model.

while they could exhibit overprecision too. This more complex pattern depends on the individual, the complexity and familiarity with the task, whether they are general knowledge questions or responses to perceptual tasks, or whether subjects have put themselves in the task or not, among other factors. Furthermore, authors like Soll (1996) find clear individual differences among subjects, some people appearing to have a bias towards reporting high levels of confidence while others in the direction of underconfidence. This will be relevant for our experimental section, since it is this more complex pattern —the differences across individuals in the three distinct measures of overconfidence— what we want to test there, in order to find out whether they might have some explanatory power over the credit policies participants implement in the strategy game —described in Chapter 8. In what follows we analyze the three measures of overconfidence suggested by Moore and Healy (2008).

5.6.1. Overestimation

The first measure of overconfidence is overestimation: people overestimate their ability, performance, level of control or chance of success —e. g., students that tend to overestimate their performance on exams. A typical question to identify overestimation across a population of individuals would be (Fischhoff et al., 1997)

> *Which city has more inhabitants? (a) Hyderabad, (b) Islamabad*
> *How confident are you that your answer is correct? 50% 60% 70% 80% 90% 100%*

Each subject would choose what she believes it is the correct answer and rate her confidence that the answer is correct. For a group of respondents, the experimenter counts how many answers in each of the confidence categories were actually correct. The typical finding is that when subjects said "I am X% confident that my answer is correct", the relative frequency of correct answers was lower (Lichtenstein, Fischhoff and Phillips, 1982).

Two discussions about these tests are in order. First, Gigerenzer (1991) claims that if after a set of questions we ask the subjects "how many of these questions do you think you got right", comparing their estimated frequencies with actual frequencies of correct answers, overconfidence disappears. Brenner et al. (1996), however, find experimental evidence that judgments of confidence at the item level and estimates of relative frequency were practically indistinguishable, both exhibiting substantial overconfidence and being highly correlated with independent judgments of representativeness. Moore and Healey (2008) relate this discussion to the vigorous debate over frequentistic versus probabilistic judgment, agreeing with Gigerenzer that there is a consensus that frequency judgments across a set of items are less prone to overconfidence than are judgments of correctness at the item-level (where participants are required to provide a probabilistic judgment). This may be consequence of the human mind being better adapted to reason frequentistically (Cosmides and Tooby, 1996).

The second discussion is about people overestimating their own skill on hard tasks but underestimating it on easy tasks. Authors agreeing this is a robust finding include Burson, Larrick and Klayman (2006), Moore and Cain (2007) and Grieco and Hogarth (2009). In order to account for these two discussions, Moore and Healy (2008) conduct their tests asking for frequency judgments across several sets of items of easy, medium and hard difficulty. We will do the same in the experimental section of this thesis. In Section 5.7 we describe in detail how we do it.

5.6.2. Overplacement

Also known as the 'better-than-average effect', overplacement refers to people considering themselves to be better than others. Perhaps the most frequently cited result is that 93% of a sample of American drivers and 69% of a sample of Swedish drivers considered themselves more skillful than the median driver in their own country (Svenson, 1981). Following that article, Shefrin (2001c) suggests a question to identify overplacement:

> *Relative to people you know, how would you rate yourself as a driver?*
> *(a) Above average, (b) Average, (c) Below average*

Several articles analyze this bias. Just to illustrate, Zell and Alicke (2011) investigate whether overplacement is related to age, Williams and Gilovich (2008) whether better-than-average effects reflect mere hopes or self-presentation, Grieco and Hogarth (2009) who concentrate on the relationship between overestimation and overplacement, and Kuyper and Dijkstra (2009), who examine the effect among secondary school students during 3 years and find strong evidence that boys exhibit more overplacement than girls and that evaluations of liking are positively related to evaluations of ability. For a further review of 'better-than-average' literature see Alicke and Govorun (2005). Again, we will implement the tests for overplacement in the experimental setting of this thesis following Moore and Healy (2008). It is described in detail in Section 5.7.

5.6.3. Overprecision

Overprecision refers to the excessive certainty regarding the accuracy of one's beliefs. According to Moore and Healy (2008), researchers examining this bias typically require participants answer questions with numerical answers (e.g., "how long is the Nile River?") and then estimate 90% confidence intervals around their answers. Results show these intervals are often too narrow (containing the correct answer less of 50% of the time). Soll and Klayman (2004) call this technique *interval estimates*, as opposed to binary choices.[178] Using binary choices causes overestimation and overprecision to be one and the same (Moore and Healy, 2008), because being excessively sure you got the correct answer from a choice of two reflects both overestimation of your performance and excessive confidence in the

[178] In binary choices participants are given questions with a choice of two answers. Then they have to pick the correct answer and state his or her confidence: e.g. "who was born first, Charles Dickens or Charles Darwin?" "Dickens – 75% sure" —Soll and Klayman (2004).

precision of your knowledge. Consequently, in our tests, in order to avoid confusing overestimation and overprecision, we study overestimation by measuring perceptions across a set of items, whereas overprecision is analyzed through a series of questions on interval estimates. We shall describe this in detail in Section 5.7. Some classic results are that overprecision is more persistent than the other two (Moore and Healy, 2008) though its presence reduces the magnitude of both overestimation and overplacement. Besides, interval estimates are prone to a great deal of overconfidence, much more than binary choice questions (Klayman et al., 1999; Juslin et al., 2000). Finally, Soll and Klayman (2004) find objective information does little to reduce overprecision.

5.7. SET OF VARIABLES, ELICITATION AND SCALING

Following the discussion above we will consider three **factors** in our experimental research, representing the three different measures of overconfidence that must be estimated. Namely:

- **Overestimation (E)**, measuring overconfidence in one's performance.
- **Overplacement (P)**, measuring a subject's overconfidence in her performance relative to the others.
- **Overprecision (M)**, measuring overconfidence in the accuracy of one's beliefs.

The section of the experiment devoted to elicit the overconfidence factors will consist of a set of trivial-like questions, devised to determine the degree of overestimation (**E**, in our notation) and overplacement (**P**) of each respondent, plus a set of additional questions where subjects are asked to provide some confidence interval estimations —devised to determine the degree of overprecision (**M**, following notation by Soll and Klayman, 2004) of each respondent. In what follows we describe the general procedure to elicit and measure the three variables, and leave the description of the specific design of the tests to Part III.

5.7.1. Elicitation

Following Moore and Healy (2008), in order to elicit the parameters **E** and **P** of each respondent, participants are required to complete a set of T trivial-like games with n-items each one. In order to account for the hard-easy effect, one half of the T quizzes should be of easy difficulty and one half of hard difficulty —though obviously this information should not be provided to participants. In each quiz, for each item participants have to mark the correct answer. Then, when they finish each quiz, they are required to estimate their own scores, as well as the score of a *randomly selected previous participant*, (RSPP). They repeat the same process for all the T rounds.

Overprecision (**M**) is analyzed in our tests through a separate set of questions where, rather than measuring perceptions across a set of items, participants are presented a series of m questions on interval estimates. Here we follow Soll and Klayman (2004) in spirit. Participants are asked to provide confidence intervals around the subjects' answers. However, Soll and Klayman (2004) show overconfidence in interval estimates may result from variability in setting interval widths. Consequently, in order to disentangle variability and true overprecision, they define the ratio

$$M = \text{MEAD}/\text{MAD}, \tag{5.16}$$

which represents the ratio of actual to ideal interval size —being MEAD the mean of the expected absolute deviations implied by each pair of fractiles a subject gives, and MAD the observed mean absolute deviation. Thus, M represents the ratio of observed average interval width to the well-calibrated zero-variability interval width. Consequently, a ratio $M<1$ indicates an overconfidence bias that cannot be attributed to random error. Soll and Klayman's studies confirm interval estimates are prone to produce substantially more overconfidence than two-point estimates, that different domains of questions are systematically associated with different degrees of overconfidence (which highlights the risks of relying on any single domain), that post-task judgments are overconfident, but less so than item-by-item judgments, and that asking subjects for three fractile estimates (two boundaries and a median estimate) rather than two reduces overconfidence.[179]

With these results in mind, the elicitation of **M** is implemented as follows. First, in each of the m questions participants are asked to specify a three-point estimate (median, 10% fractile and 90% fractile, so we have low and high boundaries for an 80% confidence interval).[180] Second, the m questions are divided into d different domains, m/d questions each, in order to make an estimation of the ratio M on each domain.[181] Most studies of confidence ask judges to draw information only from their knowledge and memory, asking traditional *almanac questions* (i.e., general knowledge questions on arbitrarily chosen topics: in which year a specific device was invented, mortality rates, etc.). Other alternatives are asking participants to make predictions based on objective cue values provided in the test (Soll, 1996) or including domains for which participants could draw on direct, personal experience (Soll and Klayman, 2004). No matter the domain, participants are required to provide a median estimate and an 80% confidence interval around their answers.

[179] One might think that making the median estimate explicit could make the anchor more salient. On the contrary, Soll and Klayman find evidence that asking for an explicit median estimate increases the size of subjective intervals.

[180] Likewise Soll and Klayman, we pretend each judge has a particular subjective probability distribution function (SPDF) for each question, and the fractiles implied by their three-point estimates provide information about those SPDFs. Whenever the judge's median estimate is midway between the two boundaries we may assume normality; however, asking subjects to provide explicitly their median estimate allows for the possibility that judges' intervals are asymmetric. In such case, Soll and Klayman (2004) recommend to use beta functions to approximate the underlying SPDF because they can approximate a great variety of skewed distributions. We will use and compare both estimations —see section 'scaling'.

[181] However, in our tests, since we can only ask a few questions and the risks of relying on a single domain were emphasized, we will choose to make only a pair of questions on three different domains. This causes a problem regarding the statistical reliability of each M estimation that will be handled in the *scaling* section below.

5.7.2. Scaling

We explain now how estimations E, P, and M for each respondent are calculated.

- **Overestimation (E)**, measuring participants' overconfidence in their own performance, is calculated subtracting a participant's actual score in each of the T trivia from his or her reported expected score, and then summing all T results. That is

$$Overestimation = E[X_i] - x_i \tag{5.17}$$

  where $E[X_i]$ is an individual's belief about her expected performance in a particular trivia test and x_i measures her actual score in that test. We calculate (5.17) for each of the T trivia, and then sum all T results. A measure E>0 means the respondent exhibits overestimation, while E<0 means underestimation. Additional information on the hard-easy effect may be available if similar estimations are calculated separately for the hard and easy tasks, in order to see if E is negative on easy tasks and positive on hard ones.

- **Overplacement (P)**, measuring subjects' overconfidence in their relative performance against others, is calculated taking into account whether a participant is really better than others. For each quiz we use the formula

$$Overplacement = (E[X_i] - E[X_j]) - (x_i - x_j) \tag{5.18}$$

  where $E[X_i]$ is an individual's belief about his or her expected performance in a particular trivia test, $E[X_j]$ is that person's belief about the expected performance of the RSPP on that quiz, and x_i and x_j measure the actual scores of the individual and the RSPP.[182] We calculate (5.18) for each of the T trivia, and then sum all T results. A measure P>0 means the respondent exhibits overplacement, while P<0 means underplacement. Again, additional information on the hard-easy effect may be available if similar estimations are calculated separately for the hard and easy tasks, in order to see if P is positive on easy tasks and negative on hard ones.

- **Overprecision (*M*)**, measuring subjects' overconfidence in the accuracy of their beliefs, is calculated by having participants specify three-point estimates for each of the m questions, and then we calculate the estimator $M = MEAD/MAD$ (see below how we do it). Here $M = 1$ implies perfect calibration, and $M < 1$ overprecision, with the higher overprecision the lower M is.

The procedure we implement to estimate M is as follows. Having a median estimate implies we should use a beta function to estimate the implicit SPDF. However, the assumption of normality serves

[182] In Moore and Healy's words, this measures the individual's belief that she is better than others, and corrects that for the degree to which she is actually better than others.

as a good approximation for a wide array of functions (Soll and Klayman, 2004). Hence, we may calculate two alternative estimations of M, one for the implied beta functions and other under the assumption of normality.

We need to estimate MEAD and MAD. First, for each question we calculate the expected surprise implied by the SPDF in order to calculate the expected absolute deviation (EAD) from the median.[183] Then, the mean of the EADs for all questions in a domain is obtained, denoted as $MEAD$. Second, for each question we calculate the observed absolute deviation between the median and the true answer, and then the mean absolute deviation (MAD) of all questions in a same domain. For M estimated with beta functions, since we have a median estimate provided by the participant, we measure MAD using that information.[184] For M estimated assuming a (symmetric) Normal distribution, MAD is calculated using the midpoint between the boundaries given by the subject. Then we calculate the ratio $M = MEAD/MAD$ for each domain. Consequently, we have so far d different estimations of the ratio (denote these m_1, m_2 … m_d). M could then simply be calculated as either the average or the median of the d different estimations. That is, we will compute four measures of M: median and average estimations for beta distributions, and median and average estimations under the assumption of normality.

5.8. CONCLUDING REMARKS

We have seen how to elicit, for a given individual and through a set of psychological tests, a series of key measures in prospect theory and overconfidence, which are the two areas of behavioral finance that will be the basis for the research in Part III. In what follows we summarize our main findings.

First, we have proposed a series of arguments in favor of setting prospect theory and overconfidence as the relevant areas of behavioral finance for our research in Part III. These include that they are two of the most-well studied areas in behavioral finance, that they are both concepts that have been suggested to explain a risk-seeking behavior, and that key concepts in prospect theory —like loss aversion or diminishing sensitivity— as well as overconfidence could help explain how misperceptions by participants in the banking sector might have led them to engage in misleading credit policies.

Second, we described prospect theory in detail, with a focus on the description of the different measures and how to calibrate them for a given individual through a set of simple questions. The measures include the risk aversion over gains, risk aversion over losses, and loss aversion for the value function, and the probability weights for the weighting function. The elicitation method seeks to

[183] For instance, the EAD of the Normal distribution is equal to $\sigma\cdot\sqrt{(2/\pi)}$. For other distributions, such as the beta function, different expressions hold.
[184] This is what Soll and Klayman do in order to later calculate what they denote the M_3 estimator.

calibrate the parameters through a simple questionnaire of three sets of questions, fifteen questions in total, based on the elicitation of certainty equivalents (Tversky and Kahneman, 1992).

Third, we followed Moore and Healy's (2008) theory of overconfidence to describe and determine how to elicit three basic measures: overestimation, overplacement and overprecision. Again, we discussed the elicitation method for the three measures of overconfidence at the individual level, which is based on the implementation of two questionnaires based on Moore and Healy (2008) and Soll and Klayman (2004).

PART III. AN EXPERIMENTAL APPROXIMATION AND THEORETICAL MODEL OF THE CREDIT CYCLE

SUMMARY OF PART III

The main goal of this thesis is to analyze the efficiency of the banking sector when granting credit to the economy. For such purpose, in Part I we reviewed a series of theories on three areas of research that revealed essential: how efficiency of the banking sector is analyzed; how efficiency is analyzed when it is referred to market-based systems; and how behavioral finance has come to defy the orthodoxy in regards to market efficiency. Part III is now devoted to provide a rationale for behavioral finance to challenge informational efficiency in bank-based systems as well. The analysis comes in three instances. First, in Chapter 6 we describe why the efficient market hypothesis as defined by Fama (1970) does not apply to bank-based financial systems. Then, we discuss how to extend the EMH to bank-based systems to analyze the informational efficiency in retail credit markets under the scope of behavioral finance. For such purpose, we suggest an alternative approach to test it that is based in the behavioral literature. This behavioral approach would be a plausible alternative to test the informational efficiency in retail credit markets, while it sidesteps the analysis of the allocative and operational efficiencies —which in bank-based systems are often affected by imperfect competition and informational asymmetries. In addition, Chapter 6 ends with a research agenda to suggest various ways the stepwise approach might be tested. Of the suggestions there provided, in the subsequent chapters we focus on the effects of prospect theory and overconfidence.

Second, Chapters 7 and 8 contribute with an experimental research performed to deal with the first step in the stepwise approach above mentioned. This experiment allows us to infer whether it is plausible to believe that participants in the banking sector may exhibit behavioral biases —namely, overconfidence and prospect theory— and the effects those biases might have over the credit policies implemented. Thus, the existence of behavioral biases is analyzed in the experiment described in Chapter 7, while the effects those behavioral biases have over the credit policies implemented by the participants in a business simulation game is described in Chapter 8. The results suggest participants exhibited different degrees of overconfidence as well as most of the classic results in prospect theory. Then, we find extensive evidence that an aggressive behavioral profile, in terms of overconfidence and risk seeking, is correlated to riskier credit strategies, in terms of providing credit to low-quality customers at a lower price. In particular, higher overprecision and distortion of probabilities for gains would foster lower prices, higher volumes of credit, and reduce quality.

Third, Chapter 9 offers a theoretical model that starts from the assumption, backed by our findings in the experimental research, that some banks in the industry are biased in terms of overconfidence and excessive optimism during the upswing of the economic cycle. In such circumstances, the second and third steps in the stepwise approach outlined in Chapter 6 are analyzed: how would a duopoly of a rational and a biased bank compete when granting credit to the economy, whether herding strategies would appear, and whether limits of arbitrage in the industry are identifiable. Our model would contribute to explain how the credit cycle is amplified due to banking competition, and makes some predictions that are consistent with the empirical observation —in particular, that the effects of the behavioral biases are more pervasive during upswings and in niche markets of low-quality borrowers.

Part III is organized as follows. In Chapter 6 we introduce a behavioral framework to analyze the informational efficiency in retail credit markets, and provide a research agenda with various alternatives to test it in the future. Chapter 7 describes the behavioral tests we performed in an experimental setting in order to obtain a basic profile of each respondent's risk attitudes and level of confidence. Chapter 8 introduces a business simulation game we devised to replicate an experimental credit market. The game is designed to replicate the basics of the decision-making process of a bank granting credit under conditions of uncertainty and risk, in order to test the relationship between the participants' behavioral profile in Chapter 7 and their credit policies in the game. Chapter 9 is devoted to provide a theoretical model of the credit cycle that shows how rational banks would herd to follow their biased competitors to grant excess credit during economic upswings. Finally, the conclusions and future investigation, as well as the appendices are relegated to the end of the thesis.

CHAPTER 6. A BEHAVIORAL FRAMEWORK TO TEST EFFICIENCY IN RETAIL CREDIT MARKETS

6.1. INTRODUCTION

The financial crisis that started in 2007 renewed attention on the role credit plays on economic cycles. Recent research suggests that credit booms are related to the business cycle. For instance, Jorda, Schularick and Taylor (2011) point out that higher rates of credit growth relative to GDP tend to be followed by deeper recessions and slower recoveries. Some explanations to this evidence that do not consider behavioral interpretations have been provided. These include incentives (Fahlenbrach and Stulz, 2011), securitization (Keys et al., 2010) and a risk-taking moral hazard by banks (Acharya and Naqvi, 2012). However, the behavioral literature may offer a simple but complementary interpretation. Since unsustainable credit and asset price booms are likely to occur in stable macroeconomic conditions (Borio and Shim, 2007), excessive optimism might had led economic agents to believe good times would last forever, revealing a financial sector unable to make a proper evaluation of demand for credit.

Since much of this credit expansion was fostered by the banking sector, there is an increasing interest among researchers to analyze the efficiency of bank-based systems. In market-based systems, the classic approach to examine efficiency is the EMH (Fama, 1970) analyzed in Chapter 2. There we saw the EMH asserts that, in competitive markets where information is available to all market participants, prices fully reflect all information available. However, imperfect competition and informational asymmetries in bank-based systems leave this approach without content. Some alternatives emerged to provide an interpretation of what determines how much credit banks should grant to borrowers: namely, the power theories of credit (Townsend, 1979; Hart and Moore, 1994, 1998) and the information theories (Jaffe and Russell, 1976; Stiglitz and Weiss, 1981) we reviewed in Chapter 1. Notwithstanding, in this chapter we suggest behavioral finance offers a simple approach to analyze the efficiency of bank-based financial systems. In particular, we introduce a behavioral approach to analyze the informational efficiency (EMH) of retail credit markets that, to the best of our knowledge, has not been proposed before. The so-called behavioral approach consists of a stepwise procedure based on Shleifer (2000) that analyzes the informational efficiency of the banking sector considering the two elements that might challenge it: market sentiment and limited arbitrage.

Along this chapter we discuss the conditions under which this approach may be easily adapted to analyze the informational efficiency of bank-based systems as well. We argue that a behavioral analysis of retail credit markets may be achieved by extending the classic EMH analysis of financial markets to bank-based systems under specific circumstances. A plausible alternative is that informational efficiency may be analyzed at a macro level and using the stepwise behavioral approach by Shleifer (2000). In short, the information theories above mentioned consider that banks, in order to provide credit to their customers, analyze the information available on items such as the economic conditions, clients' estimated solvency, and others. Thus, we may analyze the informational efficiency of such decisions —i.e., whether through banking intermediation information is transmitted efficiently in the EMH sense— by determining three features. First, whether CEOs and employees in the industry exhibit beliefs that, based on heuristics and other forms of bounded rationality, could conform a market sentiment. Second, whether market sentiment could exhibit trends or predictable patterns. Third, whether there are limits of arbitrage in retail credit markets.

In what follows we reproduce the original research where we developed this approach.[185] Section 6.2 offers a first insight to define this alternative approach. Then, Section 6.3 develops these insights on why the EMH is not applied to the banking system and how our approach would be useful to analyze the efficiency of credit policies in bank-based financial systems. Finally, Section 6.4 offers a research agenda where we suggest some alternatives to test banking efficiency following that approach.

6.2. USING BEHAVIORAL ECONOMICS TO ANALYZE CREDIT POLICIES IN THE BANKING INDUSTRY[186]

Are private banks efficient when providing credit to the economy? Probably, in the last decades there has not been such a bitter debate in academic research as the one related to efficiency in financial markets. Hence, we will not find a unanimous answer to that question, but in the midst of the worst financial crisis since the Great Depression, it seems unavoidable to wonder *how did all go wrong?*

Kindleberger (1978) provided what Shleifer (2000) named the "anatomy of a price bubble": a process that starts with some good news that generate a profit in an asset, followed by a smart-money response where both the supply and the demand of such asset are encouraged by initial investors. The bubble is then sustained by the same investors, who *"(...) stimulate positive feedback trading by (...) facilitating noise trader speculation*" (Shleifer, 2000, p.172). That is, the same agents who are benefited in the early stages of the bubble generate a greater supply of the asset and encourage other actors to

[185] In particular, Section 6.2 reproduces our first insights to define this alternative approach, which were presented in the 4th ICABE Conference in A Coruña, September 2010 (Peón and Calvo, 2010) and published as an article in 2012 by the European Research Studies Journal (Peón and Calvo, 2012a). Then, in Sections 6.3 and 6.4 we reproduce some excerpts of our dissertation presented in the 19th MFS Conference in Krakow, June 2012 (Peón and Calvo, 2012b). Since the second article extends our initial insights in the first one, we inform some similar contents are sometimes reproduced in both instances.
[186] Article published in the European Research Studies Journal, Volume XV, Issue (3)

participate, increasing the demand and sustaining asset prices until the market, eventually, collapses. Hens and Bachmann (2008) explain the anatomy of the financial bubble that led to our present crisis. They interpret the initial good news that rose prices on the real estate market as the speculative money coming into the house market after the dot-com bubble burst. Then, smart-money investors started the "*packaging of mortgage risks in new securities (MBS) that are sold outsourced in special investment vehicles (SIV) and sold worldwide*" (p.94).

That approach focuses on the role that subprime mortgages had in the process that led to the crisis, but we want to delve a little deeper into the study of how the smart-money response promoted the credit growth in order to sustain the bubble. The financial meltdown highlighted significant shortcomings on procedures used by the banking sector when providing credit to the real economy for two reasons. First, a long period of indulgence granting personal loans and mortgages boosted the credit bubble all over the world, and second, after the collapse of Lehman Brothers, an era of suspicion within the banking sector precipitated the liquidity crunch and the credit squeeze to private agents. A traditional approach to analyze market efficiency is the efficient market hypothesis (EMH) by Fama (1970) applied to capital markets. Here we will first provide a brief outlook on several ideas that behavioral economics has presented when analyzing the EMH in the context of capital markets, and then we will apply that analysis to the study of retail banking sector —both from a macro and a micro perspective— when granting credit to businesses and households.

6.2.1. Behavioral finance and the EMH in capital markets

The efficient market hypothesis (EMH) postulates market prices reflect the 'true value' of capital stock, given information available. Fama (1970) sees three categories in the EMH. Under the weak-form EMH, current stock prices fully reflect all currently available market information. Hence, past price and volume information would have no relationship with the future direction of security prices. The semistrong-form EMH assumes current stock prices adjust rapidly to the release of any market and non-market information available to the agents. Finally, the strong-form EMH version implies that prices fully reflect all public and private information. The strong-form assumes perfect markets where information is cost-free and available to all market participants at the same time.

Empirical data has challenged the EMH. Relevant examples are Shiller (1981), De Bondt and Thaler (1985), Jegadeesh and Titman (1993), Siegel (1998) or even Fama (1991) and Fama and French (1992), which evidence market anomalies inconsistent with market rationality. Empirical evidence against the weak form EMH include stock market volatility much higher than justified by the expected net present value of future dividends, extreme losers (worst performing stocks over long periods in the past) outperforming extreme winners in the short term —a sign of overreaction and return to the mean— or, on the contrary, that for short term periods price movements over six to twelve months tend to predict future movements in the same direction —known as momentum. Evidence against the semi-strong form EMH are small cap stocks earning higher returns than blue chips, or value investing (buying the cheapest stocks in terms of market to book ratios) historically outperforming growth investing. Finally, there is also evidence against the strong form EMH, particularly when markets move sharply without any apparent news.

Behavioral finance may be defined as "*the study of how psychology affects finance*" (Shefrin, 2000, preface ix). Shleifer (2000) conducts an analysis of the efficiency of capital markets under a behavioral framing. He points out the EMH is supported by three arguments which rely on progressively weaker assumptions: *"First, investors are assumed to be rational and hence to value securities rationally. Second, to the extent that some investors are not rational, their trades are random and therefore cancel each other out without affecting prices. Third, to the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices"* (p.2). The logic of the analysis is as follows. First, several psychological topics are used to analyze how agents select and process information from the market, which are their attitudes toward risk, and whether they have sensitivity to the way market information is presented to them. Through this analysis we determine whether all (or at least most) market participants do behave rationally or not. If there is evidence of agents being affected by cognition and emotional biases, this would not necessarily mean markets are not efficient. The EMH considers that if some investors are not rational, their biases will be random and hence they will trade against each other without affecting prices. Hence, behavioral analysis must determine whether irrational investors trade randomly or not.

Finally, if it is found that investors are irrational in similar ways, following some naive trends or in a correlated manner, there is a latter chance for EMH to hold. If there are rational arbitrageurs able to effectively make riskless profit from prices being out of their fundamental values, they will preserve efficiency on the market and the EMH will ultimately hold.

Investor rationality

Shleifer mentions three broad areas where people deviate from rationality —attitudes toward risk, non-Bayesian expectation formation and sensitivity to the framing of problems. However, we find more clear the approach that Shefrin (2000) used to determine that *"a few psychological phenomena pervade the entire landscape of finance*" (p.4). He distinguishes two main sources of psychological biases: heuristics (the process through which people try to find out relevant information from all news and market data) and framing biases (the fact that how a problem is presented, and not the data itself, could lead market participants taking irrational decisions).

We complete this classification with that provided by Hens and Bachmann (2008), who classify behavioral biases as those that are committed when selecting information, when processing that data, and when deciding, where framing is just one of the biases in the second group. The idea behind all of these terms is that people filter information through proxies (heuristics or rules of thumb), since market data is vast and changes every second, and that filtering process may be affected by cognitive or emotional biases. We will just mention some of them, since we later discuss in detail those that are relevant to our analysis.

Heuristic biases: availability heuristic (tendency to pay attention to pieces of information that are easier to get or understand), representativeness (reliance on stereotypes) and gambler's fallacy (tendency to see patterns in truly random sequences), overconfidence (and related concepts as illusion of control and long-shot bias), anchoring (being influenced by arbitrary —even non informative— data) and conservatism (tendency to underreact to news consistent with one's beliefs), and aversion to ambiguity (ambiguity introduces fear to the unknown). Framing biases: loss aversion (first mentioned by Kahneman and Tversky, 1979), mental accounting (problems analyzed in an isolated fashion), disposition effect (a consequence of loss aversion combined with mental accounting), house money effect (also a consequence from mental accounting), money illusion (paying attention to nominal values disregarding the effects of inflation), home bias (preference for domestic stocks), self-control and regret (two emotional biases that may affect in the decision making process).

Random irrationality

The EMH is not invalidated by the irrationality of investors: the second reasoning supporting market efficiency is that even when some investors are not rational, their trades may be random so they do not affect prices. If that is true, the strategies of the irrational investors should exhibit a lack of correlation. On the contrary, if we find some arguments supporting there is enough evidence that the cognition and emotional biases introduced above may result in a correlated behavior among irrational investors, then we might say there is odds for prices being driven out of their fundamental values. Shleifer (2000) claims that psychological evidence shows that people deviate from rationality mostly in the same direction. "*This problem becomes more severe when the noise traders behave socially and follow each other's mistakes by listening to rumors or imitating their neighbors*" (p.12).

This behavior affects not only common people, but professional investors, traders, dealers and mutual fund managers, too. Moreover, not only professional managers are subject to the same biases as individual investors, but since they manage other people's money, their decisions could be severely affected by herd instinct. In capital markets and the asset management industry it is a frequent behavior to choose portfolios that resemble the benchmark the manager is evaluated against, or to recommend stocks according to what other analysts or market consensus believe, in order to avoid a bad relative performance. Herd instinct predicts, therefore, that due to imitation, following rumors, financial gurus and recommendations on media or many other biases that are shared among investors, irrational decisions are correlated and prices could potentially not fit their fundamental values.

Limits of arbitrage

Even if irrational investors behave in a correlated manner and prices are driven out of their fundamental values, the EMH argues that the existence of arbitrageurs in the market helps correcting mispricing eventually. In capital markets there are indeed arbitrageurs that try to make a riskless profit in a market where correlated irrational investors drive prices out of their fundamental values. For that purpose, market participants having access to more complete sources of information, and through careful —and rational— research, look for mispriced stocks and try to correct them for their own profit. The central argument of behavioral economics is that, in real world, arbitrage is actually risky and limited, so even arbitrageurs —that are risk averse, have limited time period horizons and face agency problems- might not be able to ensure efficiency on markets.

Here, our analysis of credit policies in retail banking will slightly differ from that research on limits of arbitrage in capital markets. In retail credit markets, contrariwise, our first question when analyzing how banks grant credit to private agents is who might play that role of arbitrageur inside the banking industry. After we identify who could play that role, we will then analyze the limits of arbitrage in that field the same way Shleifer did for capital markets.

6.2.2. Applying BF to a new framework: Efficiency of credit policies in retail banking

We are going to consider the possibility to extend Shleifer's analysis of capital markets efficiency to a new framework: credit policies on retail banking. We delimit retail banking as the transactions from banking institutions to their customers, and credit policies as the personal loans, mortgages, credit accounts, credit cards and other credit instruments that commercial banks provide.

We will also differentiate that the allocation of credit to the real economy takes place at two levels. First, from a macro perspective, managers decide the volume of resources that each bank is ready to grant in form of loans and mortgages, according to the cost of funding in the interbank market and the macro situation they perceive both for economic growth and expected demand for credit. Credit markets are likely more complex than markets of goods and services because price is not the only variable that counts to match supply and demand. Risk is the other feature that must be considered, so banks limit their bid for each level of interest rates, allocating credit among potential customers according to the creditworthiness perceived.

Second, from a micro perspective, the decision whether to extend credit or not to each particular agent that demands it is up to both employees at commercial branches and risk analysis departments. Usually credit levels that are considered to be suitable from a macro point of view are passed down in form of commercial goals. Then, commercial success is often used as feedback when re-evaluating macro expectations. Our main purpose will be posing an alternative approach to the study of efficiency in retail credit markets and leave some open questions for future research. We will follow a three step process like Shleifer: i) do banks (managers and employees) behave rationally when granting credit to the economy? ii) are irrational policies random? iii) how may arbitrageurs ensure the financial sector provides credit in an efficient manner?

Analysis of rationality on credit policies of retail banking

What does efficiency on retail credit markets mean? In financial markets, efficiency means markets are able to accurately assess all available information in order to provide an asset price that is equal to its fundamental value. Using that approach, what should we understand by efficiency in retail credit markets? What does it mean credit institutions are rational when providing credit to the market?

The crucial role of agents in the credit market is to assess demand of credit, and with a potentially unlimited supply (under the fractional-reserve banking system, where most money in the economy is created by financial institutions, there are potentially no limits for the creation of new money other than the reserve requirements imposed by the Central Bank), decide which level of credit is supplied and who is given credit and who is not. Analyzing the rationality of retail banking when providing credit to the economy entails evaluating whether people involved in the selection process have emotional or cognitive biases, and whether these biases could make the banking sector feed speculative bubbles or provoke a credit squeeze. This debate about efficiency represents, therefore, a discussion on risk perception and prudence. Risk perception in the sense discussed above —financial institutions and authorities not appreciating the risk of an eventual collapse in the real estate market, or overweighting risks when giving credit to creditworthy agents during economic recessions—, and prudence in the sense of determining, for a potentially unlimited supply, how much credit is given to the economy from a macro perspective, and which agents will receive credit and which not from a micro point of view.

Thus, we may consider that banks analyze the credit market in two dimensions: at a macro level, they would analyze the economy and look for patterns in economic growth, its sustainability and the future demand for credit; at a micro level, it would require evaluating several aspects for credit analysis such as the candidate's credit history, the ability to pay, capital available to respond for credit, the existence or not of collateral, etc. Under that approach, we will try to identify several cognitive and emotional biases that could be reasonable observed in credit policies of retail banking both from a macro and a micro perspective. Heuristics and framing biases that have been identified in financial markets would also be relevant in retail credit markets, since those are all emotional and cognitive biases that are common to everyone. Our concern here is to point out some of them that could have a greater effect over the amount of credit, the easiness and the rationality with which credit is granted to the economy. Obviously, having empirical evidence about it would require setting a quantitative study on this area.

Shleifer (2000), for example, bases his model of investor sentiment in financial markets on two biases: conservatism and representativeness. In our opinion, conservatism could be determinant for our analysis from a macro perspective. Conservatism "*states that individuals are slow to change their beliefs in the face of new evidence*" (p. 128) and it would explain, for example, the underreaction of bank managers and supervisor authorities to evidence of credit policies fostering real estate bubbles and their latter collapse. The influence of conservatism on the decision-making process by managers and supervisors would not be quite different from the effect that it has over investors on the stock market or professional fund managers.

Representativeness, on the other hand, could be relevant from a micro point of view. Shleifer (2000) provides an idea of what representativeness means through an example: if a description of a person matches with the subject's experiences with people of a particular profession, the subject tends to significantly overestimate the actual probability that the given person belongs to that profession. Applied to our framework, if an employee working at the branches of a retail bank has had good experiences giving credit, say, to several dentists, he might exhibit a tendency to consider suitable a new potential customer only because she is a dentist. So when it comes to analyze her economic situation and creditworthiness, he could exhibit a bias to overweight good data and underestimate risks. Hens and Bachmann (2008) also relate representativeness to the phenomenon of *gambler's fallacy* (that is, the tendency to see patterns in truly random sequences). Applied to our example above, an employee working either at the branches or at the risk analysis department of a financial institution could consider that a company that exhibits very good results and a high growth in recent years (for example, a builder or a developer during the real estate bubble) will be able to maintain or even improve that performance in the future.

Two other biases that might have a relevant effect over agents at a macro level are *overconfidence* and *loss aversion* (Shefrin, 2000). Overconfidence of bank managers and supervisor authorities would have a similar impact as it has in stock markets, for example, where some agents could be overestimating the accuracy of their predictions. In financial markets this would cause prices to overreact —"*if investors are overconfident, they may overestimate the precision of their private information, causing prices to overreact*" (Hens and Bachmann, 2008, p.81)— the same way as in credit markets this could have led to a lower risk perception under a trending up real estate market. Hens and Bachmann (2008) also mention the possibility of those overconfident agents to exhibit an illusion of control. That is, judging an outcome as a consequence of their acts when in fact they have been simply lucky "*(...) even if they know that success or failure depends on chance. The greatest satisfaction, or a feeling of competence, is achieved from being able to control the seemingly uncontrollable*" (p.81).

Whereas we could use overconfidence to analyze agents' behavior when credit markets boost, loss aversion could be used to explain what happened next. That is, during recessions and due to suspicion and lack of confidence within the financial sector, bank managers become more sensitive to avoid loses than to profit from low-risk credit operations. As Kahneman and Tversky (1979) proposed in prospect theory, variance of returns becomes not a satisfactory measure of risk when agents are more sensitive to avoid losses. *"They find that a loss has about two and a half times the impact of a gain of the same magnitude"* (Shefrin, 2000, p.24). Finally, it seems reasonable that biases such as availability, mental accounting, money illusion or anchoring, among others, could also have a noticeable effect on agents both on a macro and a micro perspective.

Analysis of correlation

We have seen there are several biases that might justify why some agents may be boundedly rational. In fact, one may think that believing that every single agent in the market behaves strictly rational would be indeed too naive. Anyway, the fact that many agents in the market may not behave strictly rational is not such a challenge for the EMH, because what it matters is whether that irrational behavior is correlated amongst agents or not. Could we expect agents in retail banking be irrational in a random fashion? That would imply that while some banks are understating risks, others may behave too prudently. That is, while the former would grant loans and mortgages to satisfy almost any sort of demand they face, the latter would impose stronger restrictions than rationally required. Otherwise, if that behavior is not random across agents in the market, then we might say there are odds for an inefficient credit market.

Our objective will be to suggest some biases that could justify retail banks could sometimes exhibit correlated credit policies. We identify two different interpretations, at a macro and at a micro level. From a macro point of view, herd instinct could justify correlation. For instance, with the 2007–2008 world financial meltdown we became aware that almost every financial institution all over the globe had been trading on subprime mortgage backed securities. Another example, the stress tests by the Committee of European Banking Supervisors (CEBS, 2010) evidenced that about a 60% of the losses that the Spanish Savings Banks would experience under the worst scenario would come from real estate risks.

It is not just a matter of banks not being able to detect when they are understating risks, it is a matter that maybe they are aware of them, but not following the trend would leave them *out of the game*. Following competitors' behavior reduces risk of underperformance. Furthermore, those banks that are not willing to *play the game* (that would mean, for example, not increasing the level of credit provided to the market when all institutions are doing that) must be aware that their strategy would lead to a decline in their market share. It is quite tough for managers having to explain their shareholders why they are not making money when all the other banks in the market seem to be making it easily...

An example is Goldman Sachs, which was sued for betting against synthetic products designed by the investment bank itself and sold to their customers. That might be an evidence of some market participants being aware that risks on the market could be relevant, but still they are not willing to lose market share. Another example, after several law changes, Spanish Savings Banks faced a new scenario where they could compete against them all across Spanish market. In order to gain market share in venues away from their natural markets, many Savings Banks would probably had to take more risks during the housing boom, financing operations that local banks were not willing to finance. As this strategy would have been done by all entities willing to win market share out of their local markets, this would explain the results of the CEBS (2010) stress tests.

From a micro point of view, Milgram's behavioral studies of *obedience to authority* (Milgram 1963, 1974) could provide an interpretation. In his famous experiment, psychologist Stanley Milgram suggested that most people were able to perform acts that violate even their deepest moral beliefs: people in the experiment were required to give fake (but they were unaware of it) electro-shocks up to 450 volt to other participants in the experiment to the extent to cause them severe damages or even death. "*I set up a simple experiment at Yale University to test how much pain an ordinary citizen would inflict on another person simply because he was ordered to by an experimental scientist*" (Milgram, 1974). They were not compelled to do it under no coercive methods, only just asked to do it because it was supposed to be required for scientific purposes. He found out that relatively few people had the initiative needed to resist authority.

How could the results of the Milgram experiment explain a correlated behavior in the retail banking industry? Bank managers assess market fundamentals from a macro perspective and then transmit those levels down to their branches in form of commercial goals. Employees at commercial branches are not only required to evaluate potential demand for credit to determine whether a loan or mortgage should be granted, but they are also required to commit to those commercial goals. Under this situation, it could happen that the decision-making process would be guided by feelings rather than by rational analysis. When an employee is set some commercial goals, it could become more important to achieve them than to carefully evaluate demand suitability. Meeting commercial goals involves a personal satisfaction of *mission accomplished*, whereas not fulfilling the targets could lead to disesteem or even to some kind of punishment. The more is needed to meet goals, probably the less strict analysis on the suitability of credit will be conducted. This behavior based on emotional factors would have a greater impact when a competition among employees of the same entity is set, such that it could happen that some of them, in order to be first, focus mainly on selling more mortgages and loans than their colleagues rather than assessing risks. The rest of their colleagues will then try to follow them in order not to underperform.

Hence, a trend will be developed by the feedback effect of the commercial goals achieved: bank managers set commercial goals based on macro perspectives; employees fulfill those expectations by meeting commercial goals; and then managers evaluate again their objectives based on the belief that, since goals have been achieved, probably there is odds for more supply of credit, so new (higher) commercial goals are re-set, and the wheel keeps going on. Although it is true there is commonly a separation between business and risk analysis departments, we have on one hand that those departments are usually also set targets, and on the other hand, that frequently banks may allow —to some extent— the same people taking business decisions and evaluating risk analysis.

Finally, agents' bounded rationality may not only promote trends on credit policies, but also on the real economy. People on the market tend to trust market participants that are supposed to be better informed than average or having better resources and skills to assess the economic situation. When small investors see big companies making money in the real estate market, many of them would wonder whether to imitate them. So when they go to a bank to ask for credit and they see banks grant it without much problem, that reinforces their expectations. Thus, perhaps *herd instinct* in the financial sector fuels inefficiency not only on credit markets but also on the real economy, reinforcing overconfidence of market participants and causing further overreaction.

The role of arbitrageurs

Given market participants may sometimes be boundedly rational, and with the possibility that such behavior could be correlated across participants, there is yet one last chance for efficiency to hold in retail credit markets: finding rational arbitrageurs that are able to eliminate irrational behavior's influence. In financial markets, Shleifer (2000) analyzes whether there could be close substitutes for a given security. An arbitrageur that sees an over demanded security —say, a telecom stock— could sell that stock and buy a close substitute for that company —i.e., another telecom stock that may be seen as a fundamentally identical asset— in order to try to benefit from the mispricing of the former security.

In retail credit markets, instead, that arbitrage between close substitutes would require that a bank, after observing a mortgage that has been granted underestimating creditor risks, could make a profit by granting a new mortgage to other customer and 'short-selling' the former. That makes no sense. The risk assumed in every credit operation cannot be offset with the reduction of credit granted to any other agent in the market. Nonetheless, it might make sense to consider hedging at a macro level. That is, could we find agents in the market that will be able to rectify the excess credit provided by the banking system during credit bubbles —and the opposite when they fail to give credit— for their own profit? That role in our economies is played by Central Banks, but their function has been limited to basically setting the official set of interest rates and act as a lender of last resort for private banks. The effectiveness of Central Banks promoting stability and economic growth has been challenged several times, like nowadays. Under the fractional-reserve banking system, Central Banks do not have direct control over most of the money supply in the economy: during periods of economic growth, they can regulate the amount of credit granted to the economy through monetary policy tools —such as official interest rates, open market operations or reserve requirements[187]— but during recessions their effectiveness is limited due to *liquidity traps*[188] and *pushing on a string*[189] situations.

Could we find private agents able to play that role of arbitrageur at a macro level? We try to answer this question while going through an analysis of which properties should such an arbitrageur meet. As stated by Shleifer (2000) for financial markets, the main limit to arbitrage is that irrational effects of behavioral biases over market conditions may become much worse before they disappear. A private arbitrageur on the retail credit market would be exposed to suffer losses if market inefficiencies continue for a long time or even amplifies before they disappear. Arbitrageurs would be limited by their time horizon and their risk-aversion in a real world where arbitrage is actually risky. During periods when banks are making money by giving credit to any potential buyer, with overconfidence reigning in an apparently unbeatable economic environment, an arbitrageur should be willing not to win that easy money, quit from granting more credits and lose market share even to the point of providing no credit at all. The opposite should be done when banks stop granting credits either because they are acting irrationally or because they are trapped in a prisoner's dilemma: an arbitrageur should be willing to give credit at a lower cost when the economic environment has worsen and probably the shareholders and the managers of such private entity acting as an arbitrageur would not be keen to do so.

Since potential arbitrageurs would be commercial banks, they could also use their remuneration policy for deposits in order to arbitrage the credit market. During credit bubbles, an arbitrageur would need to raise the interest rate paid on deposits. This way, the other financial institutions in the market would be compelled to do the same, in order not to lose market share, so their cost of funding would raise and they will start imposing more stringent conditions on credit. Meanwhile, during recessions arbitrageurs should be careful with their policies on deposits. On one hand, they must pay enough to have funds sufficient to provide the credit required to the market, but on the other hand they must be aware not to tight the other banks' cost of funding in order not to worsen the financial environment.

Although we have not considered the influence of the interbank market, we might conclude arbitrage cannot be profitable: it would require paying for deposits more than required and not to be willing to earn an easy money during credit booms and the contrary during recessions. Hence, there is no incentive for private agents to do it and, even if they had the incentives, the resources needed would be enormous, because arbitrageurs should compensate the deviation that all the financial system would

---

[187] A measure almost obsolete because *"it is quite tough for economic authorities to regulate the money supply through the reserve requirements, because a mandate to increase them can be followed by a decision of the private bank to reduce its (voluntary) excess reserves, offsetting their effects"* (Antelo and Peón, 2012, p.30)

[188] A 'liquidity trap' is a situation in which Central Bank`s monetary policies become ineffective. In Krugman words, "*at an interest rate near zero the demand for money must become more or less infinitely elastic, implying that the leftmost parts of the LM curve must actually be flat. (...) Then changes in the money supply, which move LM back and forth, will have no effect on interest rates or output; monetary policy will be ineffective*" (Krugman, 2000).

[189] Pushing on a string situations are related to liquidity traps. It suggests Central Banks` monetary policies are effective slowing economic growth (Central Banks may rise interest rates, so private banks are *pulled* to cut lending) but ineffective under severe recessions, because banks tend to accumulate excess reserves and Central Banks are unable to push them to lend.

exhibit away from rationality. Therefore, contrary to what happens in capital markets, where arbitrage can be executed by any well-informed for-profit private agent in the market, it seems that arbitrage of retail credit markets could only be reserved, at most, to non-profit public entities. In our opinion, this could imply that efficiency of credit policies by the retail banking sector cannot be ensured, or at most, there would be a lower chance for this sector to be ultimately efficient —compared to capital markets— because there are no substitutes for arbitrage at a micro level, and at a macro level there would be no for-profit private agents willing to act as arbitrageurs.

In the next section we discuss more in detail how to analyze the three step process —rationality, correlation and limits of arbitrage- within retail credit markets.

6.3. DISCUSSION: A BEHAVIORAL ANALYSIS OF INFORMATIONAL EFFICIENCY IN BANK-BASED FINANCIAL SYSTEMS[190]

In this section we discuss the obstacles to use the EMH to test the efficiency of bank-based financial systems. The EMH has been extensively tested in market-based systems, but not in retail credit markets. In what follows we comment the reasons for this, and discuss how to extend the analysis of the EMH to bank-based systems.

6.3.1. The state of the art on credit markets and efficiency

Chapters 1 and 2 reviewed the academic interpretations about how banks provide credit to the economy on one hand, and market efficiency on the other. In regards to the efficient market hypothesis, we saw that the main role of financial markets —i.e., the allocation of ownership of the economy's capital stock (Fama, 1970)— requires a pricing mechanism that prices capital resources efficiently, in a way it reflects its true value. In particular, for a financial market to be perfectly efficient it must be allocatively, operationally and informationally efficient. Then, since competitive markets are, generally speaking, allocatively and operationally efficient, the debate about EMH in financial markets is actually in regards to informational efficiency. However, in bank-based systems things are not that straightforward. First, a market is allocatively efficient if it is Pareto optimal (Bouchaud, Farmer and Lillo, 2008). The first fundamental welfare theorem states that, in absence of market failures, competitive financial markets are allocatively efficient. However, bank-based systems are often an oligopoly. The parametric methods of economic efficiency (e.g. the stochastic frontier approach) mentioned in Chapter 1 are indeed used to analyze whether banks optimally respond to changes in prices of inputs or outputs.

Second, and regarding operational efficiency, a bank providing services at a price that reflects the real costs also depends on market power. Berger and Mester (1997) suggest the 'alternative profit

[190] Excerpt of the article presented at the 19th Multinational Finance Society Conference, Krakow, June 2012

efficiency' measure might be helpful: *"under conditions of market power, it may be appropriate to consider output levels as relatively fixed in the short run, and allow for efficiency differences in the setting of prices and service quality"* (p.903). Third, the analysis of informational efficiency in the banking industry is far more complex. On one hand, retail credit markets may be constrained by asymmetric information (adverse selection, moral hazard, etc.). This is indeed the main paradigm in banking theory: *"the theory of financial contracting under asymmetric information provides a general framework for understanding why smaller, information-intensive borrowers, rely on intermediaries"* (Himmelberg and Morgan, 1995, p.20). Still, on the other hand, some authors (e.g., Diamond, 1984, 1991; Fama, 1985) see financial intermediaries as efficient in evaluating, screening and monitoring borrowers, in a way they are able to solve problems of asymmetric information. Hence, banks are believed to produce valuable information regarding borrower's risk profile and quality (Godlewski, 2012).

The complexity of applying EMH to bank-based systems is not a surprise. Indeed, a microeconomic theory of banks could not exist under the Arrow–Debreu paradigm of complete contingent markets, so alternative explanations for the existence of banks had to be provided. Two alternatives are the industrial organization approach, which considers banks compete to offer services in a context of product differentiation, and the incomplete information paradigm,[191] which explains why financial markets cannot be complete (Freixas and Rochet, 1998). To sum up, allocative and operational efficiencies critically depend on the competitive structure of the banking industry. Thus, any analysis of the efficiency in bank-based systems must focus on the informational side of EMH —that is, whether prices fully reflect available information (Fama, 1970)— since allocative and operational efficiencies may not hold. Nonetheless, the analysis of the informational efficiency of the credit policies in the banking sector is still a relevant issue if we consider that, as Bouchaud et al. (2008) reckon, *"once we depart from neo-classical equilibrium a market might be informationally efficient yet allocatively inefficient"* (p.67).

The literature on the financial crisis has focused on informational asymmetries that might have made banks deviate from efficient results, including ex-ante (adverse selection), interim (moral hazard) or ex-post asymmetries (costly state verification). Here it is where our behavioral approach aims to provide a complementary element of analysis: even in a world with no asymmetric information,[192] behavioral biases might explain why bank-based systems may still not be informationally efficient.

[191] The second approach stands on various interpretations: (i) the transaction cost approach (Benston and Smith, 1976), where banks are seen as coalitions of lenders or borrowers in order to exploit economies of scale and scope in the transaction technology; (ii) the liquidity insurance approach (Diamond and Dybvig, 1983), where banks would be pools of liquidity that provide households with insurance against liquidity shocks; (iii) the adverse selection paradigm (Leland and Pyle, 1977), where there is hidden information about the quality of the borrowers that may produce scale economies in the borrowing-lending activity; and (iv) the delegated monitoring approach (Hellwig, 1991), where monitoring could improve efficiency in a context of asymmetric information.

[192] This implies that either asymmetric information does not exist, banks are able to efficiently solve them, or they operate as if asymmetries don't exist or are easy to overcome (see the power theories of credit in Chapter 1). In such case, the existence of banks would be justified by economies of scale (Benston and Smith, 1976).

6.3.2. Extending the EMH to retail credit markets: A discussion

We suggest a behavioral analysis of the informational efficiency in retail credit markets may be achieved by extending the classical EMH analysis of financial markets to bank-based systems. To show it, we first analyze under which scope the informational efficiency of bank-based systems can be analyzed following the EMH paradigm.

Capital markets are informationally efficient if asset prices fully reflect all information available and adjust immediately to any new information being published. Then, such pricing mechanism would be an unbiased predictor of an asset's intrinsic value given information available. Likewise in Chapter 2, we denote this as $E(P_{t+1}|\Omega_t)$, where Ω_t is the information set today and P_{t+1} is the security price in the subsequent period. Thus, efficient markets would be a fair game where there is no systematic difference between the actual return and the expected return before the game is played —see Eq. (2.1). In these circumstances price changes are *i.i.d.*, so the best estimate of a security return tomorrow would be its return today, $E(r_{t+1}|\Omega_t) = r_{t+1}$, and market returns would follow a random walk —see Eq. (2.3).

Testing informational efficiency in bank-based financial systems should be akin, in some way, to EMH tests in fixed income markets. Indeed, when a bank lends money to a customer, just like when an investor buys a bond, credit is granted. However, a closer look shows most similarities end there. In primary markets, the agent in need of financing issues a family of securities, each one representing both the issuer's debt with the buyer of the bond and the right of the holder to receive an interest payment until a specific maturity date. Then, the holder may go to secondary markets and trade the bond before maturity, if she is willing. Secondary markets provide both liquidity and continuous information about the expected value of these securities. Contrarily, non-marketable debt assets in bank-based financial systems are unique transactions (both in time and space[193]): no securities are —generally— issued, information analysis about the creditor's solvency goes before the bank provides the loan and, after credit is granted, the analysis of whether 'prices adjust to new information entering the markets' loses its meaning since there are no prices quoting.

How could we interpret informational efficiency in retail credit markets? An alternative might be considering each family of credit instruments as a single *security*, such that changes in the price charged to a specific type of loan (for instance, the interest rate of 30-year mortgages granted to middle-income borrowers) would represent a similar flow of information as in a security price series. However, this scope seems to be limited and not very precise in financial terms. The debate could also be extended to securitization, though this market is beyond the purposes of this thesis.

[193] We mean here that not only there are no secondary markets for non-marketable debt assets (they are 'unique in time'), but that each loan or mortgage is a specific transaction between lender and borrower, not related to any other agent. In fixed income markets each bond represents an aliquot part of the whole issue by the borrower, so an identical transaction between lender and borrower occurs for every bond; contrarily, each loan represents a transaction 'unique in space'.

A solution might emerge from the informational theories of credit outlined in Chapter 1. Banks gather and analyze information about the credit quality of their potential borrowers in order to determine whether they extend credit or not. Their goal is profit maximization given information available. At this point, the classical distinction between market efficiency from a micro perspective (that is, for the pricing of individual stocks) and from a macro perspective (for the aggregate market) becomes determinant: though tests of EMH are not applicable to bank-based systems on a borrower-by-borrower basis,[194] we could interpret informational efficiency here as how banks change their credit policies in face of new information entering the markets. It should be interpreted as follows. Would loans and mortgages granted by a bank in the past quote at a market, new information would be incorporated into prices just like in a bond market. Now, those prices are not observable, but what we may observe are the decisions banks make in response to this information. For instance, if the loan portfolio of a bank depreciates in value (reflecting a higher risk premium due to worsen economic conditions, lower credit quality of borrowers, a drop in real estate prices, etc.), changes in the bank's credit policies that account for this new information available are expected.

Those policy changes may affect three variables. First, a lower value of the credit portfolio generates potential losses that reduce capital. In order to maintain its capital ratio, a bank may issue new equity or alternatively reduce its assets. The second option would require a more conservative credit policy, reducing the volume of loans granted below the volume of existing loans being repaid. Hence, changes in value on the assets portfolio might induce changes in **volume** of new credit granted.[195] Second, new loans should be granted at 'market prices'; that is, just like new bonds are issued at a price that reflects the value of equivalent bonds in secondary markets, banks should update their credit policies for new loans in terms of **price** (interest rate, commissions, etc.) in a way they 'fully reflect the new information available at the market'. Third, since profit maximization also requires cost optimization, we might also observe changes in the bank's policy in terms of **costs** (for instance, interest rates paid on deposits, resort to financing via securitization, etc.).

---

[194] To illustrate, we may consider some of the classical tests of EMH analyzed in Chapter 2 and try to figure out how they should be applied to bank-based systems. Tests of the weak form EMH would include the analysis of serial correlation of returns and calendar anomalies, but they make no sense when applied to a context where no price series are available. Tests of the semistrong form EMH would include on one hand volatility tests, momentum versus contrary investing strategies, and the return predictability of financial ratios. All of them would require, again, a price series analysis. On the other, these test would include as well the size effect and event studies —like anomalies after earnings and dividend surprises, stock splits, SEOs and M&As. In this case, most of the events we might consider in bank-based systems would obviously be different —it does not add up now to talk about stock splits or dividend surprises, for instance— though it may make sense to analyze how events like changes in macroeconomic variables (e.g., official interest rates, GDP growth) or increases in the delinquency ratio or in household debt influence banks policies and the growth of credit within an economy. Nonetheless, those tests would only make sense from a macro perspective —again, from a micro perspective, there would be no effect over each single loan already granted. Finally, tests of the strong form EMH traditionally include the analysis of excess returns obtained by groups of investors presumed to have access to insider information (namely mutual fund managers and chief executives of companies). Translated to the banking industry, this approach may resemble the analysis performed by the 'information theories' of credit outlined in Chapter 1.

[195] It is noticeable that some authors (e.g., Biais and Bossaerts, 1998) have suggested that efficiency tests might also consider volume, as well as prices, in the context of stock markets.

Hence, a plausible alternative may be replacing the scheme $E(P_{t+1}|\Omega_t)$ of financial markets for a more general approach $E(X_{t+1}|\Omega_t)$, where X_{t+1} represents all possible strategies (price, volume, costs) a bank may change to account for new information entering the markets. Obviously, the major drawback for this approach to be implemented is that it depends on non-directly observable information: while stock prices are public data, credit policies define a bank's commercial strategy and hence we should expect them to be opaque. Beyond that, this would make any kind of time series analysis particularly unfeasible. That is why, beyond other alternative interpretations other researchers could provide here, we believe a behavioral approach could be a feasible and testable alternative for retail credit markets. The approach is based on two ideas. First, we must analyze macro efficiency for the reasons already discussed. Second, since the classic EMH tests applied to bank-based systems generally do not make sense, we will instead propose to perform this analysis under a behavioral approach, based on Shleifer (2000). We devote the next section to introduce this approach.

6.3.3. A behavioral approach to test informational efficiency in retail credit markets

We suggest that using the behavioral approach by Shleifer (2000) to test informational efficiency in retail credit markets could be a plausible alternative, while it avoids two impediments described. First, it does not require the analysis of allocative and operational efficiencies, which would depend on the market microstructure of the banking industry. Second, it largely avoids the dependence on non-directly observable information such as the commercial strategies of banks at any moment and on every credit product they sell. Instead, the analysis splits in determining whether behavioral biases influence CEOs and employees in that industry, conforming a market sentiment, whether such market sentiment could exhibit trends or predictable patterns, and whether there are limits of arbitrage in retail credit markets. This stepwise procedure goes further than simply identifying whether a market exhibits overreaction, a momentum strategy is profitable, or market participants are affected by one heuristic bias or another, but provides a comprehensive framework to test informational efficiency in bank-based financial systems, considering the two basic elements that could challenge it: market sentiment and limited arbitrage.

6.4. APPLYING THE BEHAVIORAL APPROACH TO A NEW FRAMEWORK: A RESEARCH AGENDA[196]

In this section we provide a research agenda to suggest some alternative ways to test banking efficiency following the approach introduced in the previous section.

[196] Excerpt of the article presented at the 19th Multinational Finance Society Conference, Krakow, June 2012

Credit markets are likely more complex than markets of goods and services, since price is not the only variable that matters: risk must be considered, too. Banks limit their bid for each level of interest rates, allocating credit among potential customers according to the creditworthiness perceived. Thus, in order to extend the stepwise approach to test the informational efficiency of credit policies in retail banking we might consider two possibilities. One would a demand-side analysis: e.g., why clients ask for a loan, do they behave rationally, etc. The other possibility would be a supply-side analysis: why banks grant credit, at what price, how much credit and to whom. Since whether credit is finally granted or not is up to the financial institution, we consider the supply-side more relevant and thus that is the analysis we will perform in what follows.

Under a supply-side analysis, the rationality of a bank granting credit to its potential customers depends on the role played by a series of participants. First, the rationality of the bank's board of directors, who determine the credit targets in terms of volumes of credit and prices according to the cost of funding, macroeconomic situation, demand for credit, etc. Second, the rationality of employees at commercial branches and risk analysis departments, who analyze each client's creditworthiness and determine its suitability.[197] In addition, these two factors are usually linked: credit policies by the board of directors are passed down to employees in form of commercial goals, and the commercial success is used as feedback when reevaluating future credit policies. Finally, an additional factor might be the possibility that banks find it rational to follow their competitors, even when these are biased. Tracing a correlated behavior among banks would require to analyze aggregate market variables such as volume of credit granted by each bank compared to others, the relationship among volumes, prices and default rates in the industry, etc.

In consequence, the behavioral approach we are introducing requires to identify which deviations from rationality may seem to be more plausible to explain a credit boom, following the 3-step process already described. First, do banks, managers and employees at branches behave rationally when granting credit to the economy? Second, are irrational policies random? Third, what is the role of arbitrageurs in order to ensure that the financial sector provides credit in an efficient way? The research agenda that follows tries to provide a guidance to such purpose.

6.4.1. First step: Analysis of rationality

The first step is to determine whether agents are fully rational or not. All the beliefs that, based on heuristics rather than Bayesian rationality, influence people's behavior are known as investor sentiment. Hence, the test of EMH in retail credit markets would firstly require to determine whether behavioral biases affect the decisions of managers and employees. To such purpose, in Chapter 4 we provided a taxonomy of biases and anomalies where we differentiated two basic groups —psychological

[197] Analyzing the candidate's credit history, ability to pay, capital available to respond for credit, the existence of collateral, etc.

biases and behavioral consequences. Psychological biases were classified into four categories, namely, heuristics and biases, framing, valuation/errors-of-preference and social factors, while behavioral consequences may refer to decision effects (related to individuals) or to market anomalies. In what follows we suggest some psychological biases and behavioral consequences that, in our opinion, might help explain to some extent how retail credit markets work. In each case, we provide as well a suggestion on how some tests could be performed.

Psychological biases

We identify four groups. The first group are biases that may affect how banks gather information about customers' solvency, etc. (named information selection biases by Hens and Bachmann, 2008):

Availability. It refers to the tendency to pay attention to pieces of information that are easier to get or understand. Limited attention, memory and processing capacities lead individuals to make decisions based on a subset of information, taking the probability of an event by the ease with which occurrences can be brought to mind (Kahneman and Tversky, 1973), selecting those that are easily available, more familiar or more salient. This bias is also related to attention anomalies (Shiller, 2000a) and hindsight bias (see decision evaluation biases). Tests in search of this bias in retail credit markets should be able to identify whether managers might have been unable to foresight the effects of a financial crisis, or employees of the eventual failure of many clients, just because those were highly unusual events, as Heath, Larrick and Klayman (1998) explain when they say availability effects are ubiquitous: *"A particularly important form of missing information is the absence of experience with highly unusual events. Bank examiners rarely see a bank fail, nuclear technicians rarely see a meltdown, airline personnel rarely witness a crash"* (p. 14).

The second group are biases that might affect how banks process information (known as information processing biases):

Overconfidence (and related concepts like illusion of control and self-attribution bias). As we described in Chapter 5, Moore and Healy (2008) identify three ways researchers define overconfidence: first, a person may be overconfident in estimating her own actual performance (*overestimation*); second, in estimating her own performance relative to others (*overplacement* or better-than-average effect); third, she may believe she has an excessive precision to estimate future uncertainty (*overprecision*). Applied to retail credit markets, if bank managers and supervisor authorities exhibit overconfidence it might lead to a lower risk perception under a trending up real estate market, for example, and tests should be designed to identify this possibility. Finally, overconfident agents could also exhibit in some cases an *illusion of control* —i.e., judging an outcome as a consequence of their acts when in fact they have been simply lucky— and a *self-attribution bias* (see decision evaluation biases).

Excessive optimism. Overoptimists are those who underestimate the likelihood of bad outcomes over which they have no control (Kahneman and Riepe, 1998). A classic object of research are corporate managers, whose excessive optimism would be a result of both cognitive biases (e.g., anchoring) and organizational pressures (see obedience to authority), when not of hubris: they often fall victim of a planning fallacy (Lovallo and Kahneman, 2003), exaggerating benefits and underestimating costs, overestimating scenarios of success while overlooking the potential for mistakes and miscalculations... setting themselves for a future failure. Tests applied to retail credit markets should be akin to those performed by corporate behaviorists (for a review, see Shefrin, 2006) which provide evidence that large capital investments, mergers and acquisitions, or efforts to enter new markets are classic situations where optimism pervade managers decisions, explaining the high failure rates observed.

Representativeness and **gambler's fallacy**. Representativeness basically suggests people rely on stereotypes, estimating probabilities depending on their prior beliefs (Hens and Bachmann, 2008). This may be a relevant bias in credit markets as well: if an employee working at the branches of a retail bank has had good experiences giving credit, say, to several dentists, he might exhibit a tendency to consider suitable a new potential client only because she is a dentist. Representativeness is also related to the *gambler's fallacy* (the tendency to see patterns in truly random sequences): that same employee might consider that a company exhibiting very good results and a high growth in recent years (for example, a builder or a land developer during the real estate bubble) will be able to maintain or even improve that performance in the future.

Conservatism and **anchoring-and-adjustment**. Conservatism is the tendency to underreact to new information (Shleifer, 2000), while anchoring refers to people being influenced by arbitrary and even non informative data, causing an insufficient adjustment to new information, particularly when anchors are self-generated (Epley and Gilovich, 2001). Tests should be designed to identify whether both biases can explain why bank managers and supervisor authorities underreacted to the evidence of credit policies fostering real estate bubbles and their latter collapse.

Narrow framing. It refers to the tendency to analyze problems in a specific context without broader considerations (Hirshleifer and Teoh, 2003), so when people evaluate risks they evaluate them in isolation, apart from other risks they are already facing (Barberis and Huang, 2009). Employees and executives at financial institutions might have considered each new loan in an isolated fashion, without taking into account broader effects on the level of credit already granted or the evolution of default rates in the future, and tests should check this possibility.

The third group are biases that could affect decision-making (known as decision biases):

Aversion to a sure loss (risk seeking). First identified as a reflection effect by Kahneman and Tversky (1979), this bias suggests most people are risk loving in negative domains, that is, when facing a sure loss if they do not gamble. Aversion to a sure loss is one of the biases with more empirical evidence in favor and, in our opinion, it might be one of the most relevant factors that explain what happened during the credit bubble: financial institutions might have preferred to 'gamble' (lending money to people with questionable creditworthiness) rather than assuming a loss of market share, because in that context the loans a bank chose not to grant were expected to be granted by any other institution. Loss aversion might also explain what happened next: during recessions, and due to suspicion and lack of confidence within the financial sector, bank managers became more sensitive to avoid any possible additional losses than to earn a profit from those low-risk credit operations.

Mental accounting. Closely related to framing, mental accounting is the process by which people keep track of and evaluate their transactions, just like financial accounting serves for organizations (Thaler, 2008). It provides both ex ante (how decisions are made) and ex post (how they are subsequently evaluated) cost-benefit analyses, with a relevant result: people may have multiple risk-tolerances among their various mental accounts. This might be an explanation for bank employees' risky behavior: they only considered short term results. For instance, they may be willing to take risks in order to get higher bonuses, or get promoted, though they were aware such behavior could be harmful in the long term. The effects of such behavior may be more important if commercial goals induce on the employee a higher risk tolerance (*"bosses know this business better than me"*), or if being professionally successful and getting promoted implies the employee will not be responsible of his decisions in the past (*"I don't care if it is a risky decision, I won't be here when it comes back"*).

Finally, the fourth group are of psychological biases are biases that might affect the ex-post decision evaluation (known as decision evaluation biases):

Hindsight bias. Memories can be lost or distorted, or even induced for events that never happened, so human memory must work by reconstruction (Hoffrage and Hertwig, 1999). Hindsight bias results as a side-effect: once we known the outcome of an event we exaggerate what it could have been anticipated in foresight. Biases in hindsight may explain overconfidence (Fischhoff, 1982b), particularly in retail credit markets: once they observe the first mortgages are paid regularly and the economic situation remains strong, bankers might have seen confirmed in hindsight that they did correct, their risk aversion would fall and they would keep granting more credit. However, we are aware that evidence of hindsight bias might not be conclusive, since it may also justify credit markets efficiency: now, in hindsight, we all agree *"we knew they behaved too risky when they granted those mortgages"* when, indeed, almost none of us saw that in foresight.

Biased self-attribution. It means individuals tend to attribute to their higher ability those events that confirm the validity of their actions, while evidence against it is attributed to external noise or sabotage. It has been related both to overconfidence and cognitive dissonance (Daniel, Hirshleifer and Subrahmanyam, 1998).

Behavioral consequences

Status quo effect. An effect first demonstrated by Samuelson and Zeckhauser (1988) when they found individuals tend to choose, among several options, the alternative by default, that is, doing nothing or maintaining one's previous decision. Kahneman, Knetsch and Thaler (1991) say it is a consequence of loss aversion, because the disadvantages of leaving the former alternative overcome its advantages. Applied to retail credit markets, tests should be implemented to analyze whether executives and employees chose a status quo alternative: for example, during the credit boom that alternative might have been *"to keep granting credit to anyone that asks for it"* (and the opposite during recessions).

Regret aversion (a.k.a. regret avoidance) and **cognitive dissonance**. Regret is the pain we feel when we realize we would be better off today had we chosen another option in the past (Barberis and Huang, 2009). Regret is related to cognitive dissonance —the feeling of internal tension and anxiety when two simultaneously held cognitions are not consistent— and avoiding cognitive dissonance would be equivalent to regret avoidance. If one wishes to avoid the pain of regret, it might lead to an irrational behavior: because of regret avoidance, for example, many investors renounce to sell stocks that have declined in value (a result known as disposition effect). An equivalent interpretation applied to retail credit markets would be the employee that tries to avoid the feeling of remorse for not granting a mortgage that other bank would be willing to sell —a behavior supported by Kahneman and Riepe's (1998) finding that people feel regret of things they did not, too.

Portfolio underdiversification and **home bias**. People tend to underdiversify their assets, with home bias —the preference for domestic stocks— being the classic result. First reported by French and Poterba (1991) about U.S., Japan and U.K. investors allocating 94%, 98% and 82% of their equity investments in domestic securities, home bias has been suggested to stem from familiarity (Cao et al. 2011). This is a bias easily observed in other contexts, when we observe for example that according to the European Banking Authority (EBA) 2011 stress-tests, 84% of Spanish government bonds were held by Spanish banks, 69% of Greek debt by Greek banks, 61% of Irish debt by Irish banks, and 63% of Portuguese bonds by Portuguese banks (EBA, 2011). Applied to credit markets, evidence of undiversification (for example, too much credit granted to the real estate sector) should be traced.

6.4.2. Second step: Correlated behavior

The second step analyzes whether credit market sentiment could exhibit trends, and their effect on the overall level and quality of credit granted to the economy**.** Can we expect agents in retail banking behave irrationally in a random fashion? That would imply that while some banks are understating risks, others may behave too prudently: some would grant loans and mortgages to satisfy almost any sort of demand they face, while others would impose stronger restrictions than rationally required. Otherwise, there would be odds for an inefficient credit market.

Regarding the procyclicality of credit, Borio and Shim (2007) say financial liberalization worldwide made credit booms and busts act as drivers of economic fluctuations, because an easier access to credit increases our sense of wealth and lowers risk perception. Thus, perceptions would be procyclical, reinforcing expansions and contractions, so regulation and incentive mechanisms should be implemented to correct it. Indeed, some models of bank lending take this effect into account when they consider 'switching regimes' in credit policies (see for example Azariadis and Smith, 1998; Kaufmann and Valderrama, 2008). Our purpose here is to analyze several biases that could explain why a correlated behavior in credit markets might occur.

Psychological biases

Correlated biases across the industry. The idea here is simple: if some of the biases in the first step happen to influence most market participants in the same direction, it would lead to a correlated credit market. We suggest this might be plausible for biases such as aversion to a sure loss, overconfidence, excessive optimism, or the status quo bias. For instance, aversion to a sure loss —banks willing to gamble rather than losing market share— might have been a relevant bias during the credit boom. Then, were this behavior general across the industry, it might have generated a correlated behavior —as it is now observed most banks participated in the credit bubble.

Groupthink theory and **collective confirmatory bias**. Social contagion was first evidenced in Asch's (1952) experiment, which shows the power of social pressure on individual judgment, suggesting people tend to think *"so many people can't be wrong"* when a large group of people has a particular belief, even if it strongly contradicts evidence or their own reasoning. Related to social contagion are concepts like groupthink theory, communal reinforcement and obedience to authority. Groupthink, a term coined by Janis (1972), is the tendency of cohesive groups to reach consensus without offering, seeking or considering alternative hypothesis (Lunenburg, 2010). This bias leads groups to take excessive risks, or members imposing themselves a self-censorship to avoid appearing as a dissenter or even a traitor. As a consequence, a collective confirmation bias may appear: confirmation bias, one of the most relevant judgmental bias in risk perception (Rabin, 1998) means that once forming strong hypothesis, people are often too inattentive to new information contradicting them. Thus, groupthink would be a form of collective confirmation bias (Shefrin and Cervellati, 2011), and similar tests should be implemented to determine whether it might have been a relevant factor during the credit boom.

Communal reinforcement. Related to the previous bias, early literature in social psychology about individual suggestibility, group pressure and diffusion of opinions has shown that individual opinions are influenced by others' opinion, including Katona (1901) and Asch (1952). Similar tests could be designed to analyze individual suggestibility and its effects inside the banking industry, both among employees and boards of directors.

Obedience to authority. Stanley Milgram's behavioral studies on *obedience to authority* (Milgram, 1963, 1974) may explain a correlated behavior among employees inside a bank. As we saw in Chapter 4, Milgram suggested most people were able to perform acts that violate even their deepest moral beliefs, finding that relatively few people had the initiative needed to resist authority. How could the results of the Milgram experiment explain a correlated behavior in the banking industry? Managers transmit commercial goals to employees at branches, who are not only required to evaluate each client to determine whether they can be given credit or not, but also to commit to the commercial goals they are set. Under this situation, it could happen that their decision-making process might be guided by feelings rather than by rational analysis: employees more concerned with meeting commercial goals than with carefully evaluating demand suitability.

The staff turnover's policy of a company based on fulfilling commercial goals might also represent a perverse incentive: some employees, in order to 'be first' and get promoted, might only focus on selling as many mortgages and loans as they can. If they succeed and get promoted, when default rates rise on those loans they will not bear the consequences, representing a moral hazard problem and perhaps inducing other colleagues to follow that same strategy in order not to underperform. A trend might then develop by the feedback effect of the commercial goals achieved: bank managers set commercial goals based on macro data; employees fulfill those expectations; managers re-set higher commercial goals based on the belief the business is going fine... and the wheel keeps going on, at least while default rates do not boost. Separation between business and risk analysis departments, as it is common inside banks, might help lessen the moral hazard problem; however, we must be aware that usually risk analysts are also set targets, and banks may even allow the same people taking business decisions at branches to evaluate and —to some extent— to approve their own risk analysis.

Culture. Culture are values that ethnic, religious, and social groups transmit across generations (Guiso, Sapienza and Zingales, 2006; Statman and Weng, 2010). The way people perceive the most basic events is influenced systematically by culture (Levinson and Peng, 2007). In retail credit markets cultural differences across countries regarding people's preference to own their homes rather than renting[198] might have affected banks' mortgage policies, reinforced by a bullish real estate market.

Behavioral consequences

A correlated credit market may appear in several instances, being the most relevant overreaction, momentum, herding and excessive volume. We analyze them next.

Overreaction. De Bondt and Thaler (1985) define overreaction as people's tendency to respond excessively to unexpected and dramatic events that could affect a security price. In the context of bank-

[198] In Spain, for example, there is a popular saying that goes *"properties never fall!"*, meaning real estate prices had traditionally rose, at least in recent decades. That idea might have supported the boom for some time.

based systems, overreaction might explain credit rationing the years following the collapse of Lehman Brothers. Most banks reacted the same way when the liquidity crisis started —rationing credit to the economy— but the question is: did they overreact to some extent? Did they freeze credit just because fundamentals changed, or did they even stop credit to creditworthy individuals and firms because they overreacted to bad news?

A first, but simple, approach to look for evidence of overreaction might be identifying judgmental biases that explain overreaction. Barberis and Thaler (2003) summarize the basics of the models that explain over and underreaction in three groups: beliefs (conservatism, representativeness and overconfidence), institutional frictions, and preferences (loss aversion, narrow framing). Beyond that approach, it would be better —though rather complex— to suggest alternative ways to identify overreaction in retail credit markets, similar to the tests suggested for market-based systems. However, testing overreaction in retail banking requires further analysis: De Bondt and Thaler (1985), for instance, used past returns to predict future performance, focusing on stocks that experienced extreme capital gains (winners) or extreme losses (losers) over periods up to five years, to find evidence that losers tend to be future winners. How could we apply a similar analysis to loans? Should we test volumes rather than prices? Should we use past volumes to predict future default rates?

Linking loan volumes, prices and default rates might be an alternative to test overreaction, using historical data to predict the performance of the three variables in the future. Indeed, there is literature supporting this suggestion. On one hand, in regards to financial markets, Lee and Swaminathan (2000) provide a theory to reconcile intermediate-horizon underreaction and long-horizon overreaction where past trading volume is the link between momentum and value strategies. On the other, regarding the literature on credit cycles (see Kaufmann and Valderrama, 2008, for a review) Bernanke and Blinder (1988) link credit aggregates and borrowers' costs of finance, whereas Kiyotaki and Moore (1997) relate volumes and default rates. These models could be a starting point for tests of overreaction in retail markets, but a model is yet to be developed.

Positive feedback (momentum). Jegadeesh and Titman (1993) provide evidence that markets exhibit momentum in short periods —3 to 12 months— as opposed to the evidence by DeBondt and Thaler that markets overreact during long periods —up to five years. Perhaps an equivalent scheme may be used to explain credit cycles: first, banks granted more credit year after year (positive feedback) while confidence in the economy was high, until eventually unexpected bad news came into the market (Lehman Brother's default) and banks overreacted, causing the credit crunch.

Once again, the devil is in the details: how shall we test momentum in retail credit markets? The simple alternative would be looking for evidence of biases that are said to cause a positive feedback effect (suggested in the previous point). If we wish to apply instead tests of momentum like those by Jegadeesh and Titman (1993), we would face the same problem as with overreaction: they used past returns to predict future performance, forming portfolios buying past winners and selling losers that were able to generate positive returns over 3 to 12 month holding periods. How could we do the same in credit markets? Again, we suggest literature on credit cycles as a starting point, linking credit aggregates (volumes), cost of funding (prices) and default rates: momentum in credit markets might be modeled as 'banks are giving credit at a moderate price and default rates are low, then higher levels of credit are predicted in the short term', while overreaction might be modeled as 'after longer periods of easy access to credit and high volumes of debt-to-GDP ratios accumulated, default rates are predicted to increase and, eventually, banks stop credit'.[199] However, these ideas are yet to be worked out.

Herding. Herding would be a mutual imitation (Welch, 2000), a tendency of investors to follow the herd, imitating other investors' decisions. Incentives to herd could arise endogenously because analysts herd to mimic more skilled counterparts (Scharfstein and Stein, 1990) —and so could do some banks in a follow-the-leader strategy— or because they perceive it to be a safer course of action (Jegadeesh and Kim, 2010): banks could have chosen to herd and give credit because they thought that strategy to be safer!

Herding has been related to social contagion (Shiller, 2000a), so testing for groupthink, communal reinforcement, etc. across banks could be used to have a first evidence of herding in the industry. However, it would be better to apply tests alike to those proposed by Scharfstein and Stein (1990) or Banerjee (1992). The former provides a model, based on agency problems, that is valid for corporate investment decisions (perhaps it might be so for the banking industry): distortion in incentives plays an important role in generating herd behavior, and several propositions for equilibria with reputational concerns are provided. Banerjee's (1992) sequential decision model settled the basis for future analysis of herding with no distortion in incentives (i.e., no agency problems). His model predicts that the equilibrium decision rule is characterized by extensive herding: doing what others are doing rather than using our own information is the optimal behavior, though the resulting equilibrium is inefficient.

Analyzing herd behavior within the industry would be of interest, since it might explain the 2007–2008 world financial meltdown: it is no coincidence that almost every financial institution traded subprime mortgage backed securities, or that the stress tests by the Committee of European Banking Supervisors (CEBS, 2010) shows that about a 60% of the losses the Spanish Saving Banks would experience would come from real estate investments. It is not just a matter of banks not being able to detect when they are understating risks, it is a matter that maybe they are aware of them, but not following the trend would leave them *out of the game*. Following competitors' behavior reduces the risk of underperformance, and those that are not willing to *play the game* (not selling mortgages when all banks are doing so) must be aware that this strategy would lead to a declining market share.

[199] Perhaps a correlation between failed mortgages and the period when they were granted could be traced (maybe the latter transactions were the worst ones, for example).

Excessive trading volume. Trading volume in stock markets has been suggested to be higher than it should be expected from rational investors trading for rebalancing and hedging needs (Odean, 1999), with overconfidence and reluctance to sell-short among the plausible factors behind this anomaly. Applied to retail credit markets, the volume of credit granted by the industry during the credit boom might be an evidence of an inefficient market, supported by the fact that short-selling is impossible when we are talking about mortgages and loans...

6.4.3. Third step: Limits of arbitrage

Finally, the third step would be identifying the limits of arbitrage in financial markets. The central argument of behavioral finance is that arbitrage is risky and limited because: (i) it requires close substitutes to exist, but sometimes they cannot be found (particularly the impossibility to arbitrage aggregate markets); (ii) even with perfect substitutes mispricing could become worse before it disappears; (iii) if an arbitrageur is risk averse his interest in risk arbitrage will be limited; and (iv) because of agency problems that arise under a performance based arbitrage.

In credit markets, arbitrage between close substitutes makes no sense from a micro perspective: since there are no securities, a bank observing a mortgage granted in the market that underestimates the creditor's risk would only be able to make profit out of arbitrage if it were possible to grant a new mortgage to other customer and 'short-sell' the former somehow. Besides, the risk assumed in each credit operation cannot be offset with the reduction of credit granted to any other agent in the market. Therefore, hedging should be considered in retail credit markets only at a macro level: are there market participants able to rectify the excess credit provided by the banking system during credit bubbles —the opposite with credit rationing— for their own profit? In our opinion, arbitrageurs would face the same limits as in financial markets: they would be exposed to suffer losses if market inefficiencies continue for a long time or even they amplify before they disappear, and this type of risk-arbitrage would be limited for arbitrageurs that are risk averse or in the presence of agency problems.

However, the main drawback for arbitrage to be performed by private agents is the impossibility for this strategy to be profitable: i) during credit booms, when overconfident banks are making money by giving credit to anyone who demands it, an arbitrageur should be willing not to win that easy money —in that apparently unbeatable economic environment— and lose market share; and ii) the opposite should be done during recessions, when banks stop granting credit even to creditworthy individuals, an arbitrageur should be willing to give credit even when, globally, the sector is facing a higher risk of default. Furthermore, resources required in both situations would be enormous, because arbitrageurs should compensate for the deviation the whole financial system exhibits away from rationality.

Alternatively, banks could also use their deposits for arbitrage purposes, but only with similar results: i) during credit bubbles, arbitrageurs (commercial banks) would need to raise the interest rate paid on deposits —forcing competitors to do the same— so the cost of funding rises and banks would impose more stringent conditions on credit; ii) during recessions, instead, arbitrageurs should be careful with the price they pay on deposits: they must pay enough to have the resources necessary to provide the credit required by the market, but not too high so they would tight the competitors' cost of funding and worsen the financial environment. In both cases commercial banks trying to hedge the market would be playing against their own interests, which is nonsense.

Arbitrage must be profitable at no risk or it does not work, but private banks will not have an economic motivation to hedge credit markets because that is only possible losing market share or even exposing themselves to lose money (higher default rates, higher costs of funding). Hence, the main drawback of bank-based financial systems compared to market-based ones would be that there is not a rationale for private banks to do arbitrage: ensuring informational efficiency would rely only on authorities —through regulation, central banking, public banking or other forms of market intervention. And though a positive interpretation for bank-based systems is that authorities will always try to properly arbitrage credit markets —that is, they will never behave like speculators, as it might occur in financial markets if rational investors choose to bet on the trend instead of arbitraging prices— it is also true that banks themselves could play that speculative role: the classic moral hazard problem that has been suggested to have represented a key factor in the recent crisis, specially by 'too-big-to-fail' entities (Bernanke, 2010). Therefore, a key conclusion of this analysis would be that limits of arbitrage might suggest bank-based systems are less likely to be informationally efficient than market-based ones.

6.5. CONCLUSIONS

The goal in this chapter was to set an alternative way to analyze the informational efficiency of bank-based systems. The EMH described in Chapter 2, being the classic approach to examine efficiency in market-based systems, requires markets to be fully competitive and information available to all market participants. However, bank-based systems may not satisfy those conditions, as they are often characterized by imperfect competition and asymmetric information. Some alternatives that emerged to provide an interpretation of what determines how much credit banks should grant to borrowers were reviewed in Chapter 1. Nonetheless, in this chapter we discuss how to extend the EMH to bank-based financial systems based on a behavioral approach. The main conclusions are in order.

First, any analysis of the efficiency in bank-based financial systems must focus on the informational side of EMH, since allocative and operational efficiencies may not hold. This analysis is still of interest since, once we depart from neo-classical equilibrium, a market might be informationally efficient yet allocatively inefficient (Bouchaud et al., 2008). Thus, the behavioral approach we introduce aims to provide a complementary element of analysis: even in a world with no asymmetric information, behavioral biases might explain why bank-based systems may still not be informationally efficient.

Second, we argue that the extension of the EMH to bank-based systems makes no sense from a micro point of view —i.e., on a borrower-by-borrower basis. We must analyze macro efficiency instead, interpreted —likewise the information theories described in Chapter 1— as how banks, in face of new information entering the markets, change their credit policies, which may be described in terms of price, volumes and costs —likewise the efficiency measures in Chapter 1, too. However, a major drawback for such alternative to be implemented is that prices, volumes and costs define a bank's commercial strategy, hence it depends on non-directly observable information.

Third, here the behavioral approach based on Shleifer (2000) could be a feasible and testable alternative for retail credit markets. The approach, described for financial markets in Chapter 2, may be adapted to retail credit markets as follows. We may analyze changes in credit policies and whether through banking intermediation information is transmitted efficiently in the EMH sense in three steps. First, whether CEOs and employees in the industry exhibit beliefs that, based on heuristics and bounded rationality, could conform a market sentiment. Second, whether market sentiment could exhibit trends or predictable patterns. Third, whether there are limits of arbitrage in retail credit markets.

Fourth, the chapter ends with a research agenda to suggest various ways the stepwise approach might be empirically tested, following the taxonomy of biases and anomalies provided in Chapter 4. In the remainder chapters of the thesis, we will focus on two of those suggestions, namely, prospect theory and overconfidence, to develop a formal implementation of the stepwise approach. In particular, the first step is analyzed through an experimental research described in Chapters 7 and 8: the former analyzes the presence of behavioral biases for participants in the experiment, while the latter describes the effects those biases have over the credit policies implemented by the participants in a business simulation game. Then, steps two and three are analyzed through a theoretical model of banking competition described in Chapter 9: how would a duopoly of a rational and a biased bank compete when granting credit to the economy, whether herding strategies would appear, and whether limits of arbitrage in the industry are identifiable.

CHAPTER 7. EXPERIMENTAL TESTS OF BEHAVIORAL BIASES

7.1. OBJECTIVE

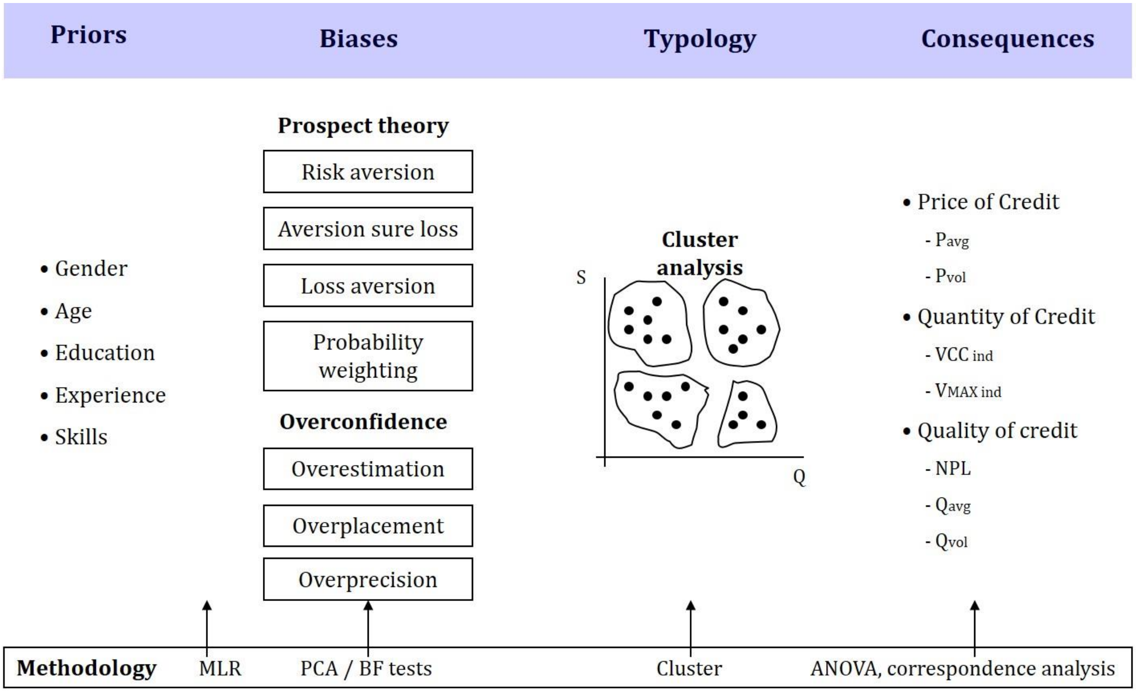
The experimental research that follows in Chapters 7 and 8 aims to test the first step in the stepwise approach introduced in Chapter 6. In particular, we focus on two relevant areas of the literature on behavioral finance, namely, prospect theory and overconfidence, described in Chapter 5, to determine two questions. First, whether the existence of these behavioral biases among a series of participants in an experimental test are identifiable, which is described in this Chapter 7.[200] Second, whether these biases could feed, among that same set of respondents, a risk-seeking behavior in a simulated credit market —which is analyzed in the subsequent Chapter 8.

For that purpose, we organized a series of five experimental sessions that took place in the Faculty of Business and Economics (University of A Coruna, UDC) during October, 2013. A group of students from different levels and degrees was selected. To make the call, which was open to the target groups, we got in direct contact with students during their classes —we thank several UDC teachers that helped during this process— to explain what the experiment would consist of, the date and time of the sessions, that they would be invited to a coffee during the performance of the tests, and that one of the tests they had to complete would consist of a game where one of the participants per session would win a prize of 60 euros.

In total 126 volunteers, all of them undergraduate and postgraduate students at the University of A Coruna, participated in the experiment divided in five sessions. All sessions took place in the computer room of the Faculty of Business and Economics at UDC. Participants in the same session completed all tests at the same time, each respondent in a separate computer. The experiment was divided in two parts. The first part was a set of questions devised to determine the psychological profile (based on prospect theory and overconfidence) of each participant. The second part was a strategy game designed to replicate, in an experimental setting, how banks grant credit to borrowers, in order to obtain information about how much credit and at what price different subjects would grant under conditions of uncertainty and risk. The outline of the experimental research that is described in Chapters 7 and 8 is summarized in Figure 7.1.

[200] This chapter reproduces an unpublished paper at the time of the writing of this thesis, available as a working paper at MPRA – Munich Personal RePEc Archive (Peón, Calvo and Antelo, 2014).

FIGURE 7.1 – Outline of the experimental research



Source: Own elaboration

Chapter 7 deals with the left-hand side of the outline above: the study of priors and psychological biases in order to obtain a basic profile (based on PT and overconfidence) of the participants in the experiment. This includes the description of the behavioral tests in the experiment, how they were designed, variables to be measured, hypotheses to be tested (regarding the effect of several priors over those variables), participants in the experiment, data and results obtained. In Chapter 8 we deal with the right-hand side of the outline above: the strategy game designed to infer how the same participants would behave when granting credit to the economy. This includes how the experiment was designed, the basics of the game, the hypotheses to be tested (regarding the effect of the behavioral variables over the outcomes of the game), how the experiment was implemented, data and results obtained.

Participants in the experiment were required to provide some basic information regarding age, working experience, etc. that was used as priors in the hypothesis testing. Some tests were then performed to obtain a basic profile of each respondent's overconfidence and risk profile. Finally, all participants competed for a prize in a simulation game where they played the role of a bank granting credit to customers. The strategies they implemented resulted in three types of indicators (price, quantity and quality of credit) for the hypotheses to be tested. Examples of documentation that were collected during the experiment sessions are attached in the Appendix. These include several application forms: (i) a participation form per session that was used to gather volunteers for the experiment; (ii) an identification form signed by all volunteers eventually participating; and (iii) an individual consent form that was required to comply with Spanish regulations in terms of privacy policy

(LOPD).[201] The 300€ in prizes (60€ per session) was funded by *Grupo de Investigación en Regulación, Economía e Finanzas* (GREFIN), application 6170109062 541A 64900.

The methodology we followed includes the behavioral tests devised to obtain the parameters describing the prospect theory (PT) and overconfidence (OC) profile of each respondent, univariate statistics (normality tests, interquartile range, etc.), bivariate statistics (correlations, ANOVAs, simple regressions) and multivariate statistics: multiple linear regressions (MLR), principal component analysis (PCA), cluster analysis, ANOVA and correspondence analysis. Supplementary statistical information is provided in the Appendix, too.

Chapter 7 is organized as follows. In Section 7.2 we describe the behavioral tests: how they were designed and variables to be measured. Section 7.3 analyzes the data obtained and compares it with results in the literature. Section 7.4 introduces the hypotheses to be tested and the results obtained. Finally, Section 7.5 concludes.

7.2. BEHAVIORAL TESTS

Participants in the experiment had to complete three different questionnaires. Firstly, some demographic information regarding age, gender, academic background and work experience. Secondly, a set of trivial-like games, devised to determine the three basic measures of overconfidence according to Moore and Healy (2008). Thirdly, a set of choices between some risky prospects and a riskless alternative, devised to determine each subject's risk-profile according to prospect theory (Kahneman and Tversky, 1979).

In what follows we provide a detailed explanation of how the questionnaires were devised and the literature that supports our choices. One goal for test design was to reduce the number of items required to estimate a specific parameter. Since participants had to complete several behavioral tests and the strategy game in Chapter 8, trying to replicate the original tests available in the literature in all its extension would be unfeasible.[202] Thus, we first discussed (see Chapter 5) the minimum number of questions to replicate the original tests to an acceptable degree. Consequently, once we obtain the data, it will be determinant to assess the quality of data we obtained by comparing our results with the average results in the literature. This will be done in Section 7.3. In what follows we describe the questionnaires.

[201] *Ley Orgánica 15/1999 de Protección de Datos de Carácter Personal, LOPD.*
[202] To illustrate, Tversky and Kahneman (1992) mention that each subject in their experiment *"participated in three separate one-hour sessions that were several days apart"* (p.305) in order to complete a set of 64 prospects, while participants in the experimental test by Moore and Healy (2008) spent *"about 90 minutes in the laboratory"* to complete 18 rounds of 10-item trivia quizzes.

7.2.1. Priors

Participants were asked to start the experiment filling a simple set of questions regarding their (a) gender, (b) age, academic background —about (c) level and (d) degree— and (e) professional experience. Table 7.1 summarizes these priors and the values they may take. A sample of the questionnaire for priors is also available in the Appendix (Table A.1).

TABLE 7.1 – Summary of priors

	Variable	Measure	Values
Priors	**Gender**	Nominal	1 = woman; 2 = man
	Age	Scale	# of years
	Level	Scale	1.0 = "1st year"; 2.0 = "2nd year"; … ; 6.0 = "6th year"; 7.0 = "Master of Science, MSc"
	Faculty *	Ordinal	1.0 = "Business and Economics (UDC)"; 2.0 = "Computing"; 3.0 = "Education"; 6.0 = "Law"
	→ ***Skills*** **	*Nominal*	*1.0 = "Others"; 2.0 = "Economics and Business"*
	Experience ***	Ordinal	1.0 = "no experience"; 2.0 = "university trainée"; 3.0 = "occasional employment"; 4.0 = "regular employm."

* Values 4.0 = "Business and Economics (USC)" and 5.0 = "Philology" were initially considered but eventually deleted as we had no observations
** This prior was not directly asked for in the questionnaires but codified using information from 'Faculty'
*** "Ocassional employment" was codified in the questionnaire as working experience with salary lower than 1,000 eur, and "regular employment" otherwise

Source: Own elaboration

7.2.2. Overconfidence

The second questionnaire was designed to measure the participants' OC based on what Grinblatt and Keloharju (2009) would call a standard psychological assessment. In particular, it was devised to obtain, for each respondent, an estimation of the three basic measures of overconfidence we described in Chapter 5, namely, overestimation ($\boldsymbol{E}$), overplacement ($\boldsymbol{P}$) and overprecision ($\boldsymbol{M}$). In order to estimate $\boldsymbol{E}$ and $\boldsymbol{P}$ we follow Moore and Healy (2008), asking participants to complete a set of four Trivial-like games. Alternatively, to estimate $\boldsymbol{M}$ we follow Soll and Klayman (2004), posing six questions where subjects are required to provide confidence interval estimations. Table 7.2 summarizes some relevant information about how to calculate and interpret all variables in the experiment, including these three measures of overconfidence.

The set of trivial games follows Moore and Healy (2008) in spirit. Indeed, several questions were taken from the original tests by the authors.[203] Answers to questions involving general knowledge tend to produce overconfidence, while responses to perceptual tasks often result in underconfidence (Stankov et al., 2012). Following this, we devised our tests asking questions of general knowledge under a time-constrained situation (150 seconds per trivial), to have a somehow mixed scenario.

[203] We would like to thank the authors for providing their tests online, they have been really helpful for the performance of our tests. We would like to be equally helpful to other researchers: a sample of the trivial tests is provided here in Table A2 of the Appendix, while the complete set is freely available at the website www.dpeon.com/documentos

TABLE 7.2 – Summary of variables in the experiment

	Variable	Measure	Values	Interpretation	Calculation	Literature
Behavioral biases	$\boldsymbol{E}$	Scale	$E > 0 \rightarrow$ Overestimation; $E < 0 \rightarrow$ Underestimation	$\uparrow E \rightarrow$ higher overconfidence	Trivia tests $\rightarrow E = \Sigma_{4\ \text{tests}}$ [E[X_i] – x_i]	Moore and Healy (2008)
	$\boldsymbol{P}$	Scale	$P > 0 \rightarrow$ Overplacement; $P < 0 \rightarrow$ Underplacement	$\uparrow P \rightarrow$ higher overconfidence	Trivia $\rightarrow P = \Sigma_{4\ \text{tests}}$ [(E[X_i] – E[Xj]) – (x_i – xj)]	Moore and Healy (2008)
	$\boldsymbol{M}_{med}$	Scale	$M > 1 \rightarrow$ Underprecision; $M < 1 \rightarrow$ Overprecision	$\downarrow M \rightarrow$ higher overconfidence	I.C. $\rightarrow m_i$ = MEAD / MAD $\rightarrow M_{med}$ = median 3 domains	Soll and Klayman (2004)
	$\boldsymbol{M}_{avg}$				I.C. $\rightarrow m_i$ = MEAD / MAD $\rightarrow M_{avg}$ = average 3 domains	
	$\boldsymbol{\alpha}^{+}$	Scale	$\alpha^{+} > 1 \rightarrow$ convex utility, $\alpha^{+} < 1 \rightarrow$ Concave util. (GAINS)	$\uparrow \alpha^{+} \rightarrow$ higher risk seeking (GAINS)	PT questionnaire → Elicitation of certainty equivalents power value & Prelec-I weighting fns. non-linear regression	Kahneman and Tversky (1979) Rieger and Wang (2008) Tversky and Kahneman (1992) Abdellaoui et al. (2008)
	$\boldsymbol{\alpha}^{-}$	Scale	$\alpha^{-} > 1 \rightarrow$ concave utility, $\alpha^{-} < 1 \rightarrow$ Convex util. (LOSSES)	$\downarrow \alpha^{-} \rightarrow$ higher risk seeking (LOSSES)		
	$\boldsymbol{\gamma}^{+}$	Scale	$\gamma^{+} \leq 1 \rightarrow$ distortion of probabilities (GAINS)	$\uparrow \gamma^{+}$ (gains of high prob.) $\rightarrow$ higher risk seeking		
	$\boldsymbol{\gamma}^{-}$	Scale	$\gamma^{-} \leq 1 \rightarrow$ distortion of probabilities (LOSSES)	$\uparrow \gamma^{-}$ (losses of low prob.) $\rightarrow$ higher risk seeking		
	$\boldsymbol{\beta}_{med}$	Scale	$\beta > 1 \rightarrow$ Loss aversion	$\uparrow \beta \rightarrow$ higher loss aversion	observed certainty equivalent → median 3 questions	Hens and Bachmann (2008) Booij et al. (2010)
	$\boldsymbol{\beta}_{avg}$				observed certainty equivalent → average 3 questions	
Credit policy – Indicators	$\boldsymbol{P}_{avg}$	Scale	$P^* \rightarrow$ min 10.0% - max 20.0%	↓ Price → higher risk strategy	average price across 6 niche clients	
	$\boldsymbol{P}_{vol}$	Scale			volume-weighted average price across 6 niches	Defining the relevant indicators of the game: Berger and Mester (1997)
	$\boldsymbol{VCC}_{ind}$	Scale	$VCC_{ind}^* \rightarrow$ min 0 - max 500	↑ Volume → higher risk strategy	average volume of credit granted (6 niches)	
	$\boldsymbol{VMAX}_{ind}$	Scale	$VMAX_{ind} \leq 1$ where $VMAX_{ind} = 1 \rightarrow$ full credit at P^*		$VMAX_{ind} = VCC_{ind}$ / ($\Sigma_{6\ \text{niches}}$ [V_{max} | P*])	
	$\boldsymbol{NPL}$	Scale	% of non-performing loans (min 0%)	↑ NPL → higher risk strategy	average *ex post* NPL ratio across 6 niche clients	Design and measurement of indicators: own elaboration
	$\boldsymbol{Q}_{avg}$	Scale	$Q_{avg} < 1 \rightarrow$ lower P to risky niches (Opt.$_{expost}$ Q_{avg} = 1.119)	↓ Quality → higher risk strategy	average prices to costumers of high vs. low qualities	
	$\boldsymbol{Q}_{vol}$	Scale	Idem (Opt.$_{expost}$ Q_{vol} = 1.117)		idem, volume-weighted	

Source: Own elaboration

In each of the four rounds, respondents took a 10-item trivia quiz. A sample of questions from those quizzes is provided in Table A.2 in the Appendix. A pair of quizzes had a topic on 'cinema, music and sports' and the other pair on 'geography, history and science' (this information was given to participants), while each topic included one easy and one hard difficulty quiz —though this information was not provided to them. At the start of the questionnaire, participants were provided the following information. *"In what follows you will respond to a series of tests similar to the classic Trivial game. You will have to complete 4 Trivial of 10 questions each, two on topics 'cinema…' and two about 'geography…'.* ***Important****: the goal of the test is not to measure your knowledge, but to measure the ability of people to maximize their abilities and knowledge under stressful situations, and to self-evaluate their performance. For such purpose, each of the four tests will be performed under a time limit of 150 seconds, at the end of which, when time is over, you will be asked to self-evaluate your performance."*

Obviously the purpose of the test was not "to measure the ability of people to maximize their abilities and knowledge under stressful situations" but to measure the participants' overconfidence. To foster this perception, they were recommended to respond first to the questions they think they knew better, because they might run out of time to complete the entire test. Prior to solving the trivia, participants were asked to answer a practice question to familiarize with the experimental setting. Then they took the actual quizzes. In each quiz, for each item they had to mark the correct answer. Then, when the time was over, they were required to estimate their own scores, as well as the score of 'a randomly selected previous participant' (RSPP).[204] Finally, they repeated the same process for all the other three rounds in the questionnaire.

After the four trivia tests were completed, participants were asked six additional questions (see Table A.3 in the Appendix), where they had to provide some confidence interval estimations. These six questions have been devised to determine their degree of overprecision following Soll and Klayman (2004) in spirit. We implemented this test as follows. First, in each of the six questions we ask participants to specify a three-point estimate (median, 10% fractile and 90% fractile, so we have low and high boundaries for an 80% confidence interval).[205] Second, Soll and Klayman ask a set of several questions per domain to make an estimation of $\boldsymbol{M}$ on each domain. However, since we can only ask a few questions and the risks of relying on a single domain were emphasized in Chapter 5, we choose to make only a pair of questions on three different domains. This causes a problem regarding the statistical reliability of each $\boldsymbol{M}$ estimation that was discussed in Chapter 5.

[204] They were required to estimate 'the average score of other students here today and in similar experiments with students of this University'.

[205] Just like Soll and Klayman, we pretend each judge has a particular subjective probability distribution function (SPDF) for each question, and the fractiles implied by their three-point estimates provide information about those SPDFs. Whenever the judge's median estimate is midway between the two boundaries we may assume normality; however, asking subjects to provide explicitly their median estimate allows for the possibility that judges' intervals are asymmetric. In such case, Soll and Klayman (2004) recommend to use beta functions to approximate the underlying SPDF because they can approximate a great variety of skewed distributions. We will use and compare both estimations —see section 'scaling'.

The six questions of this set are provided in Table A.4 in the Appendix. Questions 1 to 4 are traditional *almanac questions* —i.e., general knowledge questions on arbitrarily chosen topics— on two different domains. The first domain consisted of two questions about 'the year in which a device was invented', the second one about mortality rates —a classic question in the literature regarding shark attacks (see Shefrin, 2008b) plus another one regarding road accidents in Spain.[206] Questions 5 and 6 try an alternative approach. Most studies of confidence ask judges to draw information only from their knowledge and memory. Soll and Klayman introduce two variations: the first one by Soll (1996), in which participants are asked to make predictions based on objective cue values provided in the test; the second variation, they include domains for which participants could draw on direct, personal experience. We choose the second one to ask questions 5 and 6, again inspired by Soll and Klayman, on 'time required to walk from one place to another in A Coruña at a moderate (5 km/h) rate without interruption'. Participants were required in all six cases to provide a median estimate and an 80% confidence interval around their answers.

With the answers provided in the trivia tests and confidence interval questions we may compute an estimation of $\boldsymbol{E}$, $\boldsymbol{P}$ and $\boldsymbol{M}$ for each participant. How to do those estimations was explained in Chapter 5. In brief, overestimation ($\boldsymbol{E}$) of a given participant is calculated subtracting her real score in each trivia from her reported expected score and summing all 4 results, following Eq. (5.17). Overplacement ($\boldsymbol{P}$) is calculated following (5.18), which takes into account the participant's beliefs about her expected performance compared to the others, as well as the actual scores of both the individual and the RSPP.

Finally, overprecision ($\boldsymbol{M}$) is defined as $M = MEAD/MAD$ following Eq. (5.16). We calculate an estimation of M for the beta functions implied by the 3-point estimation provided by the respondent.[207] We proceed as follows. For each question we calculate the expected absolute deviation (EAD) from the median and the observed absolute deviation (AD) between the median and the true answer. Then, for each pair of questions per domain we compute $MEAD$ as the mean EAD, MAD as the mean AD, and $M = MEAD/MAD.$ Consequently, we have three different estimations m_1, m_2 and m_3. M could then simply be calculated as either the average or the median of the three estimations.

We want to compare median and average estimations for the following reason. Notice we use only two questions per domain (Soll and Klayman used twelve). This may generate distortions: if a judge happens to provide an answer to a question that is very close to the true answer, MAD ≈ 0 and M $\to \infty$, which would distort our mean estimation M across domains. Consequently, a key analysis in Section 7.3 will be to compare these and other measurement alternatives and to discuss whether it would be necessary to include more questions per domain in future research.

---

[206] The Spanish *Dirección General de Tráfico*, DGT, provides the statistics of road accidents in Spain at the website http://www.dgt.es/portal/es/seguridad_vial/estadistica/accidentes_24horas/evolucion_n_victimas/

[207] Additional measures of *M* were estimated assuming normality. Further information in subsection 7.3.1.

7.2.3. Prospect theory

The purpose of the third questionnaire is to measure the value and weighting functions, according to prospect theory, for each respondent. Recall in Chapter 5 we chose to use a parametric approach with a power value function —Eq. (5.8)— and Prelec-I weighting function —Eq. (5.10)— where decision weights are normalized according to NPT. Hence, we have five parameters (α^+, γ^+, α^-, γ^- and β) that we must estimate per respondent. Our method merges some characteristics of Tversky and Kahneman (1992)'s approach to elicit certainty equivalents and Abdellaoui, Bleichrodt and L'Haridon (2008)'s proposal to make an efficient test with a minimum number of questions. In particular, the methodology we use is based on the elicitation of certainty equivalents of prospects involving just two outcomes —a classic approach by Tversky and Kahneman (1992). To obtain the cash equivalents, we ask respondents a series of refined choice questions. Following Abdellaoui et al. (2008), the elicitation method consists of three stages, fifteen questions in total: six questions involving only positive prospects (i.e., a chance to win some positive quantity or zero) to calibrate α^+ and γ^+, six questions for negative prospects to calibrate α^- and γ^- and three questions regarding the acceptability of mixed prospects, in order to estimate β.

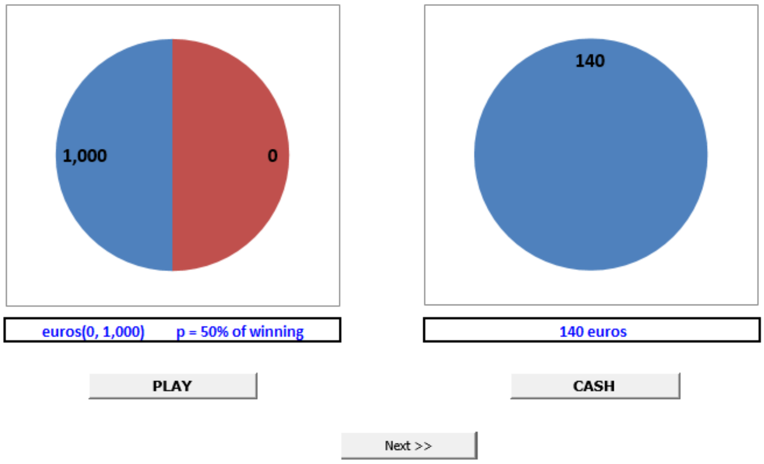
Some aspects were considered in all three stages. First, utility measurements are of interest only for significant amounts of money (Abdellaoui et al., 2008) while utility is close to linear for moderate amounts (Rabin, 2000).[208] Hence, prospects devised to calibrate α^+, γ^+, α^- and γ^- used significant, albeit hypothetical, amounts of money of 500, 1.000 and 2.000 euros —with all outcomes in euros and multiples of 500 euros to facilitate the task (Abdellaoui et al., 2008). Second, only the three questions devised to estimate β used small amounts of money for reasons already described —see the problem with loss aversion in Chapter 5. Consequently, with the aim of preventing the possibility that asking the larger amounts in first order might affect the perception of the smaller amounts in the β elicitation, those three questions were asked in first order. Finally, prior to solving any trial, respondents were asked to answer a practice question to familiarize them with the experimental setting. Instructions emphasized there were no right or wrong answers (Booij, van Praag and van de Kuilen, 2010), but that completing the questionnaire with diligence, always providing objective and honest answers, was a prerequisite to participate in the strategy game (Chapter 8) where they would compete for a prize.

The first three questions, regarding the acceptability of a set of mixed prospects, were then provided to participants in sequential order. Specifically, respondents were asked *"someone offers you a bet on the toss of a coin. If you lose, you lose X euro. What is the minimal gain that would make this gamble acceptable?"*,[209] where *X* took the values 1 euro, 10 euros and 100 euros in the first, second and third iterations, respectively. Posed this way, all questions to calibrate loss aversion set probabilities of

[208] This is consistent with the results we obtained in our pre-test: we used amounts of money of about 1.000 euros that we felt significant enough for students; however, when tests were implemented to university professors, some of them told us they felt the amounts were quite low and hence they could exhibit a riskier-than-normal behavior.
[209] Inspired by Hens and Bachmann (2008), p. 120.

success and failure equal to 50%, $p = 0.5$. In the second stage a set of six questions involving only positive prospects was provided, again in sequential order. Figure 7.2 shows one of the six iterations participants had to answer. Participants had also time to practice a sample question.

FIGURE 7.2 – A sample question with positive prospects



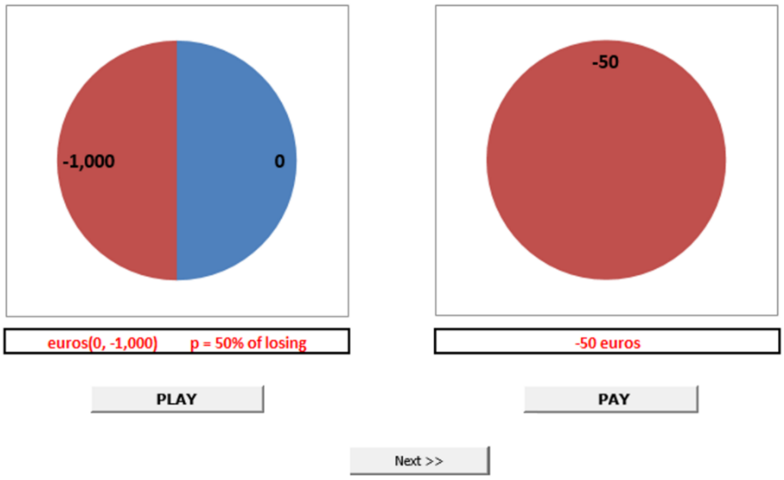
Source: Own elaboration

In every iteration participants had to choose between a positive prospect (left-hand side) and a series of sure positive outcomes (right-hand side). Information was provided in numerical and graphical form. Every time the subject answered whether she preferred the prospect or the sure gain, a new outcome was provided. This process was repeated until the computer informed the respondent that the question was completed and she could continue with another prospect. The probabilities of success in all 6 prospects were different (two questions with probability 50% and one question with probabilities of success 99%, 95%, 5% and 1% each), which was emphasized to participants to avoid wrong answers. The series of sure outcomes per prospect were removed from two sets, following Tversky and Kahneman (1992) in spirit: the first set logarithmically spaced between the extreme outcomes of the prospect; the second one linearly spaced between the lowest accepted amount and the highest rejected in the first set. Table A.4 in the Appendix summarizes both sets for all questions in the questionnaire. All sure outcomes were rounded to a multiple of 5 to facilitate the task. Following Abdellaoui et al. (2008), to control for response errors we repeated the last sure outcome of the first series at the end of each trial, allowing to check the reliability of the responses.[210] The certainty equivalent of a prospect was then estimated by the midpoint between the lowest accepted and the highest rejected value in the second set of choices. Tversky and Kahneman (1992) assert this procedure allows for cash equivalents to be derived from observed choices, rather than assessed by the subject.

[210] Abdellaoui et al. (2008) repeated two iterations: "the first iteration after the final iteration" for all questions, and "the third iteration" of 2 questions for gains and 2 for losses, chosen randomly. They obtain 96% reliability for the first iteration, 66% for the third one, and claim them to be satisfactory. We repeat the last outcome in the first series (somehow similar to a 'third iteration') of all questions for gains and losses. Hence, having similar results (66% to 96%) will be considered reliable.

Finally, the third stage included a set of six questions involving only negative prospects, designed to calibrate α^{-} and γ^{-} parameters. We proceeded similarly. Figure 7.3 shows one of the iterations.

FIGURE 7.3 – A sample question with negative prospects



Source: Own elaboration

Participants had time to practice a sample question. We emphasized prospects and sure outcomes were now in terms of losses, and that probabilities were in terms of probabilities of losing, which may be change along prospects (similar probabilities were provided, namely 1%, 5%, 50%, 50%, 95% and 99%). Certainty equivalents were now estimated as the midpoint between the lowest (in absolute terms) accepted value and the highest (in absolute terms) rejected value in the second set of choices.

7.3. ASSESSING DATA QUALITY

The behavioral tests we devised follow some previous tests in the literature. However, most of them were very large in duration required to complete them. Considering we needed participants in our experiment to complete both types of behavioral tests, plus the experimental game in Chapter 8, shorter versions were required. Consequently, the main motivation of this section is to assess the reliability of the behavioral parameters that were estimated with our method. We do this in two instances. First, we conduct a preliminary analysis of data for a raw data matrix description, estimation of some basic univariate statistics, and detection of outliers and extreme values. Second, we conduct an analysis in order to determine the goodness of the results obtained compared to regular results in the literature.

Table A.5 in the Appendix shows the raw data we obtained given all the participants' responses, whereas Table A.6 shows the estimations that result (priors, OC measures and PT parameters) according to the estimation procedures described in Chapter 5. First thing to note, using the frequency tables about priors summarized in Table 7.3, are some pros and cons of our experimental group.

TABLE 7.3 – Frequency tables for priors

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	60	47.6	47.6	47.6
	Male	66	52.4	52.4	100.0
	Total	126	100.0	100.0	

Faculty

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Economics & Business	105	83.3	83.3	83.3
	Computing	18	14.3	14.3	97.6
	Education	1	.8	.8	98.4
	Law	2	1.6	1.6	100.0
	Total	126	100.0	100.0	

Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No experience	64	50.8	50.8	50.8
	University trainee	29	23.0	23.0	73.8
	Occasional employment	23	18.3	18.3	92.1
	Regular employment	10	7.9	7.9	100.0
	Total	126	100.0	100.0	

Skills

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Others	21	16.7	16.7	17.5
	Economics & Business	105	83.3	83.3	100.0
	Total	126	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	17,0	1	.8	.8	.8
	18,0	11	8.7	8.7	9.5
	19,0	12	9.5	9.5	19.0
	20,0	11	8.7	8.7	27.8
	21,0	18	14.3	14.3	42.1
	22,0	22	17.5	17.5	59.5
	23,0	22	17.5	17.5	77.0
	24,0	14	11.1	11.1	88.1
	25,0	5	4.0	4.0	92.1
	26,0	3	2.4	2.4	94.4
	27,0	3	2.4	2.4	96.8
	28,0	2	1.6	1.6	98.4
	31,0	1	.8	.8	99.2
	53,0	1	.8	.8	100.0
	Total	126	100.0	100.0	

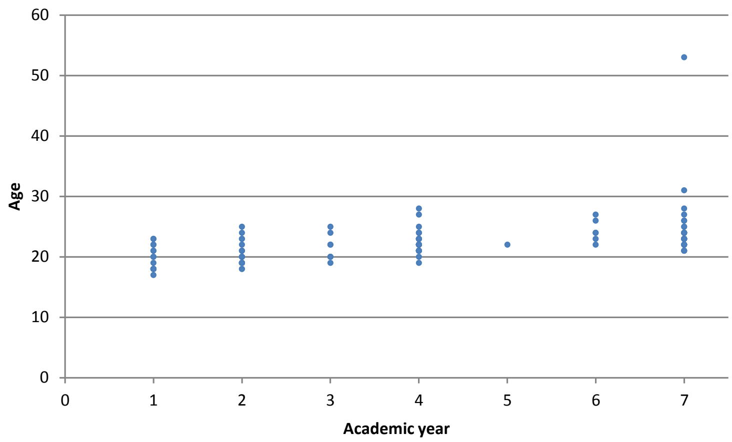
Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1st year	19	15.1	15.1	15.1
	2nd year	24	19.0	19.0	34.1
	3rd year	8	6.3	6.3	40.5
	4th year	33	26.2	26.2	66.7
	5th year	1	.8	.8	67.5
	6th year	6	4.8	4.8	72.2
	MSc	35	27.8	27.8	100.0
	Total	126	100.0	100.0	

Source: Own elaboration

On the positive side, the group is balanced in terms of gender, as well as in terms of age and academic year within the bounds of our selection (see Figure 7.4). Besides, we introduced a subgroup of 21 students that have no degree in economic or financial studies to serve as contrast.

FIGURE 7.4 – Participants. Age to academic year ('level')



Source: Own elaboration

On the negative side, all participants are students from UDC, what makes the experimental group limited in terms of age (98.4% of them were between 17 and 28 years old). Besides, in subsection 7.4.2 we will see that age, academic year (level) and professional experience are correlated in this group. Moreover, level is not a good proxy for education: in the literature, it is intended to measure levels such as 'no education', 'primary education', 'secondary education', and so on; however, our selection consists only of university students, hence level measures only university studies and is highly correlated with age. These problems will be a drawback for our hypothesis testing in Section 7.4.

TABLE 7.4 – Descriptive statistics of the behavioral variables

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Age	126	36.00	17.00	53.00	22.15	3.72	13.825	4.704	.216	37.433	.428
Level	126	6.00	1.00	7.00	4.04	2.22	4.918	.155	.216	-1.400	.428
E	126	28.00	-8.00	20.00	2.93	4.76	22.643	.790	.216	1.529	.428
P	126	27.00	-13.98	13.02	-2.71	4.69	21.959	.302	.216	.785	.428
M_{med}	125	1.50	0.00	1.50	0.34	0.26	.066	1.841	.217	4.902	.430
M_{avg}	125	1.32	0.07	1.38	0.46	0.29	.085	1.310	.217	1.837	.430
alpha +	126	2.43	0.24	2.67	1.02	0.46	.213	1.513	.216	2.482	.428
alpha -	126	2.24	0.05	2.29	0.52	0.31	.098	2.320	.216	9.199	.428
gamma +	126	0.95	0.05	1.00	0.64	0.26	.065	-.163	.216	-.700	.428
gamma -	126	0.95	0.05	1.00	0.53	0.28	.077	.183	.216	-1.147	.428
β_{med}	126	9.40	0.60	10.00	3.01	1.97	3.897	1.599	.216	3.182	.428
β_{avg}	126	26.00	0.67	26.67	3.64	3.57	12.750	3.978	.216	20.157	.428

Source: Own elaboration

In what estimations for the behavioral variables is concerned, Table 7.4 summarizes the basic univariate statistics. We may see overprecision measures M_{med} and M_{avg} have only 125 observations. This is due to missing responses by one participant at that test, as it will be explained in subsection 7.3.1.

Most variables (all but overplacement at 5% significance) do not satisfy the hypothesis of normality, as it may be observed in Table 7.5 below. This is not a surprise for two reasons. First, the group comprised students at UDC of all ages and levels. Hence, these two priors are more likely to resemble a uniform, rather than a normal, distribution. Second, with the only exceptions of E and P, most behavioral indicators are bounded (to 0 all of them, and also to 1 the gammas) and some of them are expected to be asymmetric —as underprecision or loss aversion range from 1 to infinite, for instance.[211]

TABLE 7.5 – Normality test for the behavioral variables

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Age	.190	126	.000	.666	126	.000
Level	.187	126	.000	.859	126	.000
Overestimation	.133	126	.000	.955	126	.000
Overplacement	.079	126	.054	.979	126	.047
Overprecision 1	.134	125	.000	.854	125	.000
Overprecisión 2	.127	125	.000	.891	125	.000
alpha +	.197	126	.000	.861	126	.000
alpha -	.134	126	.000	.821	126	.000
gamma +	.126	126	.000	.940	126	.000
gamma -	.090	126	.013	.949	126	.000
loss aversion 1	.203	126	.000	.832	126	.000
loss aversion 2	.217	126	.000	.606	126	.000

a. Lilliefors Significance Correction

Source: Own elaboration

Such boundaries and asymmetries must be considered when analyzing outliers. Table A.8 in the Appendix provides a normal Q-Q plot and a box-and-whiskers plot for all variables. According to this, we proceed as follows. First, we will consider only to exclude extreme values, not outliers.[212] However, we will only exclude them when the normality tests suggest these values may indicate experimental error rather than high kurtosis. Second, we will use these refined estimations for the hypotheses testing in Section 7.4. In the analysis below we have considered all variables without exclusion as the purpose of this section is to analyze the goodness of the tests implemented. These rules being considered, four observations have been removed from two variables: one extreme value for age and three for loss aversion (β_{avg}). Besides, in subsection 7.3.2 we will discuss some individual observations that might represent experimental errors in the elicitation of PT parameters.

[211] For further interpretation, Table A.7 provides the histograms of all variables in the experiment.

[212] The box plots in Table A.8 in the Appendix use SPSS statistics, which identify outliers as data beyond the whiskers of the plot (which represent 1.5 times the height of the box), and extreme values as data beyond three times the height of the box.

Finally, regarding the goodness of tests, we intend to assess the reliability of the results in this experiment compared to the regular results in both the theoretical and empirical literature. Indeed, the concern to design tests that are shorter and more efficient is a classic in the behavioral literature (e.g., Abdellaoui et al., 2008), since they would enhance the scope for application of concepts like prospect theory or overconfidence. We conduct this analysis separately for each section.

7.3.1. Goodness of tests on overconfidence

We analyze the goodness of tests devised to estimate ***E*** and ***P*** on one hand, and ***M*** on the other, as we used different tests in both instances.

*Trivial tests (indicators **E** and **P**)*

Participants completed the four trivia in about 15 minutes, instructions included. There were no relevant incidents in any of the five sessions: respondents declared a perfect understanding of instructions, all responses were coherent and there were no missing values of any kind. Finally, the results obtained regarding the estimations on indicators ***E*** and ***P*** support the tests were designed satisfactorily for the following reasons.

First, participants on average exhibited overestimation (clearly) and underplacement. Thus, the average respondent overestimated her performance in the trivia by 2.9 right answers (out of 40 questions in total). This bias was also persistent in both easy and hard tests. In addition, the average respondent considered herself below average by -2.7 correct answers, with the bias being mostly attributable to an underplacement in hard tasks. These findings are consistent with most literature supporting a general bias towards overestimation of one's abilities (e.g., Lichtenstein, Fischhoff and Phillips, 1982; De Bondt and Thaler, 1995; Daniel, Hirshleifer and Subrahmanyam, 2001) except on easy tasks or in situations where success is likely or individuals are particularly skilled (Moore and Healy, 2008), as well as towards underplacing one's performances relative to others on difficult tasks (Moore and Small, 2007) or being generally pessimistic about winning in difficult competitions (Windschitl, Kruger and Simms, 2003). Table 7.6 summarizes average data in the experiment.

TABLE 7.6 – Overestimation and overplacement

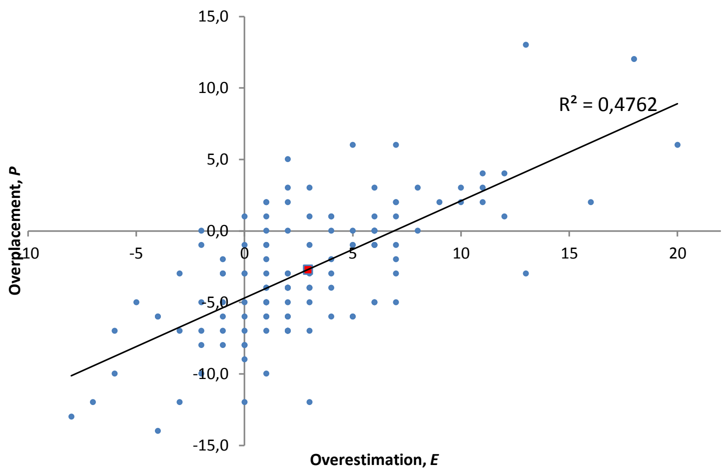
	T1	T2	T3	T4
self estimation (average)	6,6	2,7	3,8	5,9
self estimation (median)	7,0	2,5	4,0	6,0
estimation of others (average)	6,4	4,0	4,8	6,4
estimation of others (median)	6,0	4,0	5,0	6,0
right answers (average)	**5,40**	**2,29**	**2,75**	**5,58**
right answers (median)	**5,0**	**2,0**	**3,0**	**5,0**

	ALL	Easy	Hard
Overestimation	**2,9**	1,5	1,4
Overplacement	**-2,7**	-0,3	-2,4

Source: Own elaboration

Also relevant is the strong correlation that appears between variables ***E*** and ***P*** (see Figure 7.5 below). That is, though the biases along the experimental group are towards overestimation and underplacement, participants that exhibited the highest overestimation tend to consider themselves above average (or, at least, featured a lower underplacement) and vice versa. This would support the interpretation of overestimation and overplacement as "interchangeable manifestations of self-enhancement" (Kwan et al., 2004; Moore and Healy, 2008).

FIGURE 7.5 – Correlation between *E* and *P*



Source: Own elaboration

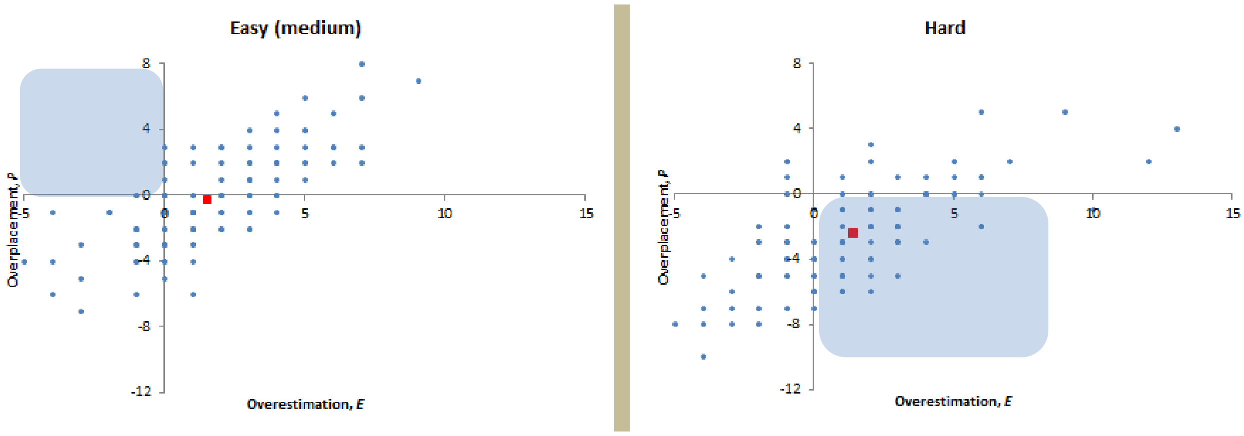
Finally, the trivia tests were indeed devised to control for the hard–easy effect. However, that design did not work well enough as the results suggest we failed to propose a couple of easy tests that participants find them as easy as we expected. We may see in Table 7.6 above that trivia tests T2 and T3 had average (median) correct answers of 2.29 (2.0) and 2.75 (3.0) out of 10 questions. Considering correct answers attributable only to good luck would represent a coefficient of 2.0,[213] it shows participants found these tests hard indeed. Trivia tests T1 and T4, instead, were expected to yield correct answers of 7.0 to 8.0 on average,[214] but respondents only hit the right answer 5.4 (5.0) and 5.58 (6.0) out of 10 questions on average (median). This would represent a couple of tests of a medium —rather than an easy— difficulty for respondents. In any case, we find results are good for hard tests and coherent with literature for easy (medium) tests, since overplacement reduces from -2.4 in hard tests to about zero in easy ones, while overestimation does not increase (supporting the finding that a general bias towards overestimation is appreciated). Figure 7.6 next helps to appreciate this effect more clearly.

---

[213] Each test consisted of ten questions with five possible answers each. Hence, participants had a probability of 20% to hit the right answer by chance, making it 2.0 right answers out of 10.

[214] Those were the results obtained in a pre-test with similar questions performed by several volunteers. We attribute the eventual differences between the experiment and the pre-test to differences in age and experience between both samples (for instance, volunteers in the pre-test included teachers as well as students, and elder people might had better clues for a right answer in questions about events that happened decades ago). Otherwise, readers may also attribute it to researchers' overconfidence.

FIGURE 7.6 – The hard–easy effect



Source: Own elaboration

As we may see, most observations for the hard tests —graph on the right-hand side of Figure 7.6— meet the mentioned tendency towards overestimation, underplacement, or both. For tests with a medium difficulty —graph on the left-hand side of Figure 7.6— the general drift upwards is noticeable (meaning that lower levels of underplacement for easy tests are general along the group), while overestimation is similar on average but with less observations towards higher levels. Furthermore, it is also clear that the correlation between overestimation and overprecision mentioned above exists in both instances.

To sum up, we consider that a test similar to those implemented by Moore and Healy (2008) but with only four trivia sets (two hard and two easy) of 10 questions each and 5 possible answers per question is satisfactory in terms of simplicity (low time-consuming, only about 8 minutes per indicator) and efficiency (quality of results in accordance to academic literature) to provide individual measures of overestimation and overplacement. Nonetheless, two features might be improved in future research. First, a better design of easy tests such that they meet the required standards for a hard-easy effect. Second, the general drift towards overestimation in the experiment might be lessened introducing questions on abilities and perceptual tasks (Stankov et al., 2012), as the time constraint and a couple of questions on mathematical logic introduced as a variation from Moore and Healy (2008)'s original tests seem not enough for that purpose.

*Test on confidence intervals (indicator **M**)*

Participants completed the six questions on confidence intervals to infer their individual degree of overprecision (estimator ***M***) in about 6 to 8 minutes, instructions included. Though test results show a vast tendency towards overprecision —perhaps the most evident result of all in the experiment— that is supported by most empirical findings in the literature (e.g., Jemaiel, Mamoghli and Seddiki, 2013), we are concerned about the reliability of the estimations obtained at the individual level. We will later explain why; for now let us analyze the main results obtained.

First, judges were significantly overconfident. The aggregate results show a strong tendency to overprecision: the 80% confidence intervals contained the correct answer only 38.3% of the time. This is much higher than the 14% overconfidence observed by Soll and Klayman (2004) for three-point estimates and about the same level than for a range estimate. Overconfidence varied across domains as it was expected: the lowest degree of overprecision corresponds to the domain where participants could draw on personal experience (time to walk from one place to another). However, they were still overconfident: 80% intervals hit the right answer 62.0% of the time. When the M ratios are estimated to account for the effects of variability, overprecision becomes even more prevalent: almost 75% of respondents exhibit overprecision ($M < 1$) in the domain with the lowest level of overconfidence ('time to walk') and 97.6% in the highest ('how many deaths'). Finally, when these results are added up to calculate a single ratio M per judge we have between 93.6% and 97.6% of them exhibit overprecision, whether we use average or median estimates, respectively. Table 7.7 summarizes all the results.

TABLE 7.7 – Overprecision

Domain		Hit rate*		***M***	***"M₂"***
Invention dates			Invention dates		
	Q1	12.0%	median	0.28	0.26
	Q2	51.2%	average	0.36	0.37
	Average	**31.6%**	M < 1 (%)	**94.4%**	**94.4%**
Number of deaths			Number of deaths		
	Q3	17.6%	median	0.10	0.10
	Q4	24.8%	average	0.21	0.17
	Average	**21.2%**	M < 1 (%)	**97.6%**	**99.2%**
Walk times			Walk times		
	Q5	66.4%	median	0.64	0.58
	Q6	57.6%	average	0.82	0.81
	Average	**62.0%**	M < 1 (%)	**74.4%**	**79,2%**
MEDIAN			M < 1 (%)	**93.6%**	**98.4%**
AVERAGE		**38.3%**	M < 1 (%)	**97.6%**	**96.8%**

* Answers that exactly matched an endpoint were counted as correct

Source: Own elaboration

Two classic results are that overprecision is more persistent than the other two types of overconfidence (Moore and Healy, 2008), though its presence reduces the magnitude of both overestimation and overplacement. Our results are in accordance with the first regularity, while the second one will be tested in Section 7.4. With this general drift towards overprecision, suffice to say that this bias is clear for both genders and different ages (again, more information is provided in Section 7.4). Finally, we use Soll and Klayman (2008)'s alternative refinement[215] to estimate M to see overprecision is mainly attributable to narrow size intervals. As we may see in Table 7.7, when ratio M is estimated

[215] The original refinement is the one we seen: doing the estimates of MEAD and MAD based on more flexible representations of participants' SPDFs (i.e., the beta function that better fits the three estimations provided by the respondent). Alternatively, Soll and Klayman (2004) suggest we may measure MAD assuming the median is in the middle of the distribution —using only the two endpoints and assuming a symmetric distribution). The authors denoted M_3 the first measure and M_2 the second one.

assuming the median is in the middle of the distribution rather than using the participant's response (denoted *M_2* in the authors' notation) overprecision slightly increases. This means most participants with an asymmetric SPDF tended to provide median estimates that reduced the errors (at least to some extent). This result is coherent with Soll and Klayman's empirical finding that three-point estimates reduce overconfidence.

Although results on aggregate seem to be consistent with empirical literature, we are concerned about the reliability of the estimations obtained at the individual level. In particular, we are concerned for several reasons. First, there is evidence that several participants did not understand the instructions. Since we did not expect this section to be particularly problematic, the computer application was not prepared to avoid missing values or incoherent responses.

In the first season we had several incidents: a respondent did not complete all three answers per question; some had problems to interpret that questions of the type *"I find it equally probable that it is higher or lower than…"* were asking for a median value; others had problems to correctly interpret that *"more than (after year)…"* and *"less than (before year)…"* were asking for a minimum and a maximum interval bound. Consequently, we had observations where minimum and maximum boundaries were swapped, where answers were provided in some particular order (e.g., lower – medium – higher value) when responses were presented (and recorded) as median – lower – higher, or where the median estimation was identical to any of the boundaries.

In following seasons we tried to avoid these incidents by emphasizing in the instructions that all three questions were required and providing a fictitious example of what we were asking for. Though things improved significantly (we did not have more missing values and the percentage of respondents that exhibited some kind of error clearly declined) we still had some incoherent answers. Fortunately, we could contact participants by e-mail days after the tests were performed to ask them to confirm their answers. This way, errors of the kind swapped boundaries or responses in a particular order could be amended. Others instead, like missing values or median estimations identical to any boundary, were not modified as it would represent an alteration of the experiment results.

In order to avoid these incidents in future research, we suggest to enhance Soll and Klayman (2004)'s approach with two modifications. First, by setting the order of estimates in terms of lower bound – median – upper bound. According to the authors, *"if order of estimates has effects, they are complex ones"* (p.311), which supports our suggestion that a specific order will not bias the results but helps respondents to better understand the task.[216] Second, we believe a picture or a table would help, such that participants are required to fill three boxes in the specific order —as in Table 7.8.

[216] In addition, we might consider the possibility to clearly state we are asking for a median estimate (we are not sure whether Soll and Klayman avoided this intentionally), though this option might introduce an asymmetry as it would represent a better clue for those respondents more familiar with statistics.

TABLE 7.8 – A suggestion to avoid incidents in future research

In which year was the telegraph invented?

I am 90% sure that the year is after	I think the year is as likely to be after this year as before it	I am 90% sure that the year is before
lower bound	median estimate	upper bound

Source: Own elaboration

A test enhanced with these suggestions should help to confirm whether the general bias towards overprecision observed in the experiment is correct. In any case, we claim this bias does not emerge from a misunderstanding by participants of the concept 'confidence interval' or what the purpose of the tests was: instructions clearly stated and emphasized that these questions were intended to *"assess your ability to make estimations with a high degree of confidence"* and that minimum and maximum answers should be provided *"in order to be 90% sure that you hit the right answer"*. Consequently, rather than having a problem with results on aggregate, the main problem we find with the test is in the reliability of individual estimations, summarized in Table 7.9.

TABLE 7.9 – Reliability of individual *M* estimations

	M_{beta}		M_2		M_{normal}	
	M_{med}	M_{avg}	M_{med}	M_{avg}	M_{med}	M_{avg}
range	0.0 - 1.5	0.07 - 1.38	0.0 - 1.59	0.05 - 3.08	0.02 - 4.89	0.08 - 19.68
median	0.31	0.40	0.3	0.38	0.40	0.51
average	0.34	0.46	0.34	0.45	0.51	0.94

		M_{beta}	M_2	M_{normal}
median vs. average	variation*	0.10	0.09	0.09
	threshold**	52.0%	47.2%	45.6%
	change sign***	4.0%	2.4%	9.6%

		median	average
across methods	variation*	0.09	0.12
	threshold**	46.4%	54.4%
	change sign***	4%	12.8%

* measured as the median of the individual variations

** percentage of individuals for which the difference (in absolute terms) between median and average estimation of M are larger than 0.10

*** percentage of individuals for which ratio *M* ranks the same individual as being both over- and underconfident depending on whether we use median or average estimations

Source: Own elaboration

This reliability problem comes from the evidence that individual estimations of ratio *M* depend on the refinement method used to estimate *M* and whether indicators are computed as the median or the average of the m_i values across domains. In particular, we compare three different refinement methods (the two already described and a third one where both MEAD and MAD computations assume a normal distribution for each participant's SPDF),[217] and for each of them we computed the individual indicator M as either the mean or median of the ratios across domains. We get the results in Table 7.9. First, the last refinement method that assumes normality yields the most extreme results. We will later explain this effect is not a problem of this method in particular but an evidence of the weakness of the test itself. Second, indicators that are computed as the average of ratios across domains are higher. This happens as mean estimations are highly dependent on extreme values when the items (only three domains here) are very few. Third, if we compare how many individuals have an estimator that varies substantially[218] whether we use medians or averages, we find about half of the individuals would have an indicator that is highly sensible to the estimation method. This effect is particularly pervasive when M ratios yield qualitative results that are conflicting: i.e., when we have the same individual could exhibit overprecision (M<1) or underprecision (M>1) depending on the method we consider. This happens to 4% of participants in the standard refinement of M and up to 9.6% in the worst case. Finally, if we do this comparison across refinement methods[219] (instead of median vs. average) we obtain similar results.

This reliability problem is particularly puzzling for the hypothesis testing in Chapter 8, since there we will be using M indicators as independent variables that are not robust to different methods of estimation. Why this happened? Basically, because in our search for a simplicity–efficiency equilibrium we heeled heavily over simplicity: we designed the tests with only two questions per domain and this revealed to be not enough. When only having two questions per domain, providing an answer to a single question that is close to the true response strongly affects the eventual estimation of M.[220] Besides, given the nature of the reliability problem, average estimations tend to be less reliable than median estimations. Though this effect is more palpable in the case of the refinement method that assumes normality, this only happened by chance. In particular, there were a few respondents (basically only four) for which the middle point of their inferred symmetric SPDF for a particular question happened to be very close to the true answer. Would this happen instead with the median answer provided by the judges, the effect would be more palpable for the original M indicator we are using as option-by-default.

In future research some amendments will be required for a test of this kind to be a short one without prejudice to obtain efficient results. Having more questions per domain will be essential, but with the restriction of devising a test that is not highly time-consuming for a single indicator. A

---

[217] The two methods already described are the option-by-default, which uses MEAD and MAD from the inferred individual SPDF fitted with a beta function, and estimator M_2, where MAD assumes a symmetric distribution.
[218] We consider a 'substantial variation' of 0.10 in absolute terms between median and average estimations. Since median estimations of M in the different methods are about 0.40, a variation of 0.10 would represent an estimation that varies about 25% depending on the method we use —which we consider a variation that is substantial enough. Given this variation is basically equivalent to the median variations observed along the experimental group for the three refinement methods (0.09 – 0.10 according to Table 7.9), it is not a surprise that we had in all cases about half the individuals affected by a sensible measure.
[219] Given we have three different refinement approaches, we have done this comparison across methods by analyzing the minimum and maximum estimations we get for each individual using any of the three methods.
[220] If median estimation and true answer are close, AD will be near to zero. When only having two questions per domain, the estimator m_i = MEAD / MAD for that domain will be strongly biased upwards. Consequently, since we have only considered three domains, median and (particularly) average estimations of the individual's indicator M will be severely affected.

sensibility analysis may be performed to a list of 3 to 5 questions per domain to calibrate which option would better balance the simplicity–efficiency tradeoff. Besides, given our results support the regular evidence that domains where participants can draw on personal experience exhibit the lowest degree of overconfidence, it may be preferable to ask questions on one additional domain. This way we would have two domains on almanac questions and two on personal experience to equilibrate. This should also be helpful to balance individual M estimations when they are computed as a median or an average across domains. Given participants in our tests required about 5 minutes (plus instructions) to complete a test of 6 questions, asking 16 questions would require about 15 minutes in total, which we consider a limit for a test for only one indicator to be brief enough.

Finally, another interesting option for future research is to repeat similar (enhanced) tests with the same group of participants as in this experiment. We mean not only to compare results for M, but for E and P indicators in the trivia tests as well. This would contribute to the literature on debiasing. With that goal in mind, we should first explain to participants what was the purpose of these tests, what were their answers and biases they exhibited in this experiment, and then let them perform the new tests. How will they behave? Will participants correct their biases? Will they overreact?

7.3.2. Goodness of tests on prospect theory

This section analyzes the goodness of our method to measure the value and weighting functions of each respondent. Based on the elicitation of certainty equivalents of prospects involving just two outcomes under a normalized prospect theory approach (Rieger and Wang, 2008a; Hens and Bachmann, 2008) for the scaling of parameters, and assuming parametric specifications that are widely supported in the literature, our method merges some characteristics of Tversky and Kahneman (1992)'s approach to elicit certainty equivalents and Abdellaoui et al. (2008)'s proposal to make an efficient test with a minimum number of questions. In order to fit all properties of the value and weighting functions, fifteen questions were asked —three per parameter. Fifteen questions seem hard to be reduced: the elicitation requires some questions to estimate beta, others to estimate the distortion of probabilities close to 0 and 1, for probabilities about 50% to obtain further information on utility curvature, and in any case a mix of questions for positive and negative domains is required. Participants in our experiment completed the fifteen questions in about 20 minutes, instructions included, and there were no relevant incidents in any of the five sessions.

Though the empirical validity of prospect theory has been largely tested, how to elicit the value and weighting function for a given individual does not come without controversy, as we discussed in Chapter 5. Moreover, the controversy exacerbates if estimations are made imposing specific parametric functions and the number of questions are minimized. However, the results of this experiment evidence our tests replicate the main findings on prospect theory. In particular, we support the validity of our method based on several analyses, both at the individual and aggregate level: (i) properties of the value and weighting functions; (ii) the fourfold pattern of risk attitudes; (iii) iteration and fitting errors; (iv) anomalies detected at the individual level. We explain these analyses in detail in what follows.

Value and weighting functions

Table A.5 in the Appendix shows all participants' responses to the fifteen questions in the test. Table A.6 in the Appendix shows the estimations that result for individual parameters $\alpha^+, \gamma^+, \alpha^-, \gamma^-$ and β. Results obtained at the aggregate level are described with four measures: the average and median of parameters estimated at the individual level, and the parameters estimated for the average and median participant. Table 7.10 provides the results at the aggregate level.

TABLE 7.10 – PT parameters at the aggregate level

	individual parameters		idealized participant		Main results in the literature*	
	median	average	median	average		
α^+	0.93	1.02	0.96	0.91	- T&K'92: $\alpha^+ = 0.88$ - Abd'08 review: 0.70 to 0.90 - Abd'08 results: $\alpha^+ = 0.86$ - Abd'07: $\alpha^+ = 0.72$	- W&G'96: $\alpha^+ = 0.48$ - Stott'06: $\alpha^+ = 0.19$ - Donk'01: $\alpha^+ = 0.61$ - Booij'10: $\alpha^+ = 0.86$
α^-	0.44	0.52	0.43	0.50	- T&K'92: $\alpha^- = 0.88$ - Abd'08 review: 0.85 to 0.95 - Abd'08 results: $\alpha^- = 1.06$	- Abd'07: $\alpha^- = 0.73$ - Donk'01: $\alpha^- = 0.61$ - Booij'10: $\alpha^- = 0.83$
γ^+	0.63	0.64	0.60	0.52	- T&K'92: $\gamma^+ = 0.61$** - Abd'08: $\gamma^+ = 0.46 - 0.53$ - W&G'96: $\gamma^+ = 0.74$	- Stott'06: $\gamma^+ = 0.94$ - B&P'00: $\gamma^+ = 0.53$ - Donk'01: $\gamma^+ = 0.413$
γ^-	0.50	0.53	0.58	0.40	- T&K'92: $\gamma^- = 0.69$** - Abd'08: $\gamma^- = 0.34 - 0.45$	- Donk'01: $\gamma^- = 0.413$
β_{med}	2.00	3.01	2.00	3.04	- T&K'92: $\beta = 2.25$ - Abd'08 review: 2.24 to 3.01 - Abd'08 results: $\beta = 2.61$	- Abd'07: $\beta = 2.54$ - Booij'10 review: 1.38 to 1.63 - Booij'10 results: $\beta = 1.6$
β_{avg}	2.67	3.64	2.33	3.51		

* Authors mentioned: T&K'92 (Tversky and Kahneman, 1992); Abd'08 (Abdellaoui et al., 2008); Abd'07 (Abdellaoui et al., 2007); W&G'96 (Wu and Gonzalez, 1996); Stott'06 (Stott, 2006); B&P'00 (Bleichrodt and Pinto, 2000); Donk'01 (Donkers et al., 2001); Booij'10 (Booij et al., 2010)

** These research articles imposed a different parametric specifications other than Prelec-I for the weighting function

Source: Own elaboration

We also compare our results in Table 7.10 against some classic results in the literature.[221] Most empirical estimations of utility curvature support prospect theory's assumption of concavity for gains (α^+ from 0.7 to 0.9 in most studies) and convexity for losses (α^- from 0.7 to 1.05),[222] with more recent studies tending to provide empirical estimations that are closer to linearity in both instances (Booij et al., 2010). Our results reiterate these findings for gains, while risk seeking in the negative domain seems to be much higher (this assertion will be later qualified). The percentage of individuals with alpha measures below one are 59.5% (α^+) and 93.7% (α^-).

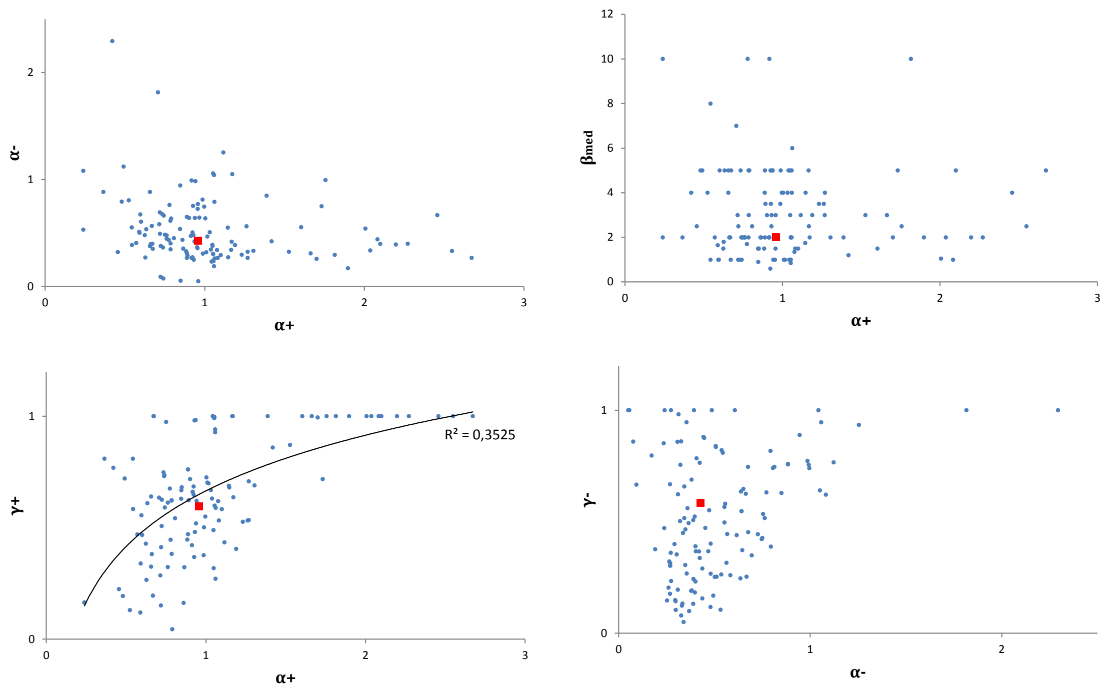
[221] Results provided for comparison include Tversky and Kahneman (1992), Abdellaoui, Bleichrodt and Paraschiv (2007a), Abdellaoui et al. (2008), Wu and Gonzalez (1996), Stott (2006), Bleichrodt and Pinto (2000), Donkers, Melenberg and van Soest (2001) and Booij et al. (2010). More information about other authors, as well as results for other parametric specifications, are available in extensive summaries provided by Stott (2006) and Booij et al. (2010).

[222] Note these pieces of evidence would be equivalent to risk aversion for gains and risk seeking for losses if weighting function is linear, but more complex risk profiles may arise when the curvature of both functions are taken together (see Chapter 5).

We observe a significant degree of probability weighting in both domains —with higher distortions in the negative side— and quantitative estimations (about $\gamma^{+} = 0.6$ and $\gamma^{-} = 0.5$) are in consonance with literature. By using Prelec-I function we are imposing the classic inverse S-shaped weighting function observed in most studies (that is, the non-linear regressions set the restrictions $\gamma \leq 1$). Notwithstanding, there seems to be no debate here since aggregate indicators are significantly below one and most individual observations (78% for gains, 91% for losses) fitted better for gamma values below one (here we computed all respondents with $\gamma^{+}, \gamma^{-} < 0.95$).

Parameters α^{-} and γ^{-} suggest a strong risk seeking behavior in the negative domain by most participants. There may be two interpretations that are not mutually exclusive. First, the main drawback of experimental tests is that gains and losses are hypothetical. Though instructions emphasized the importance of trying to imagine situations as real, the results might suggest most participants were unable to fully interpret the consequences of playing a game in the negative domain. In particular, several participants were strongly biased in terms of probability weighting (the minimum observation is $\gamma^{-} = 0.05$ and one third of the sample is below the lower bound in the literature, 0.35) and most of them exhibited a utility curvature α^{-} below 0.50. Second, this biased profile by some individuals suggest they might be better described with a weighting function that accounts for elevation as well as curvature, like Prelec-II (see 'anomalies at the individual level' for more information). Besides, since α^{-} and γ^{-} are fitted simultaneously using data in the negative domain, this might also affect α^{-} estimations —which are below regular results in the literature, as we noted above.

FIGURE 7.7 – Correlation of parameters



Source: Own elaboration

Figure 7.7 plots the correlation across participants of some parameters in the value and weighting functions. Red dots in all graphs are the parameters estimated for the median respondent. Graph at the top-left shows there seems to be a negative correlation between alpha parameters (hence, individuals that are more risk seeking in the positive domain tend to be risk seeking in the negative domain as well). Graph at the top-right shows no apparent correlation between α^{+} and β. Finally, there seems to be a positive correlation between alpha and gamma parameters, particularly significant in the positive domain. Section 7.4 provides complete results of statistical tests for these and additional correlations.

Finally, our beta estimations are in consonance with classic results in the literature (a loss aversion higher than 2) compared to more moderate estimations reported by Booij et al. (2010). The percentage of individuals with beta measures above two are 73.0% for β_{med} (65.7% of individuals if β is estimated as the respondent's average answer) and only 14.3% have $\beta \leq 1$ (7.9% using β_{avg}).

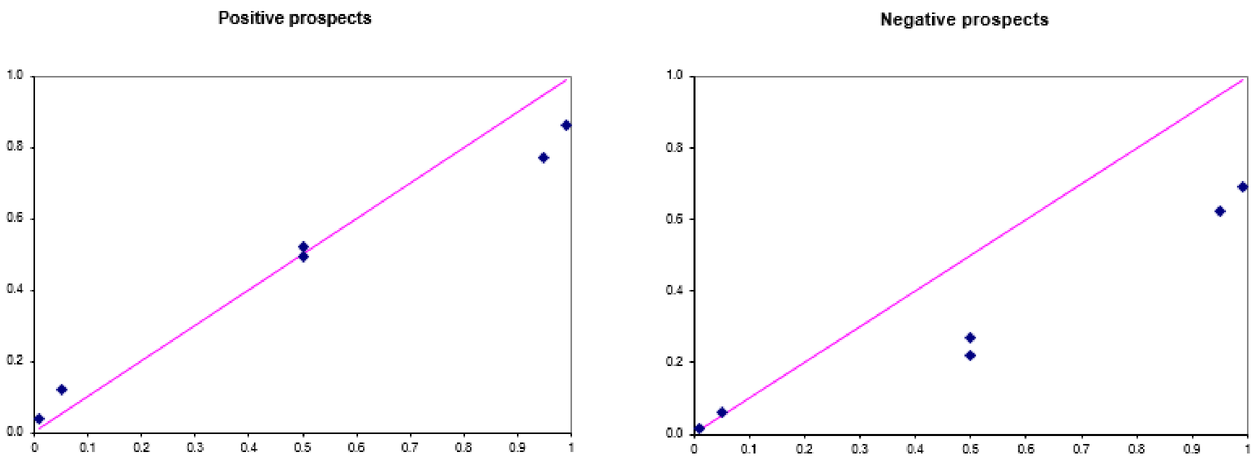
The fourfold pattern of risk attitudes

Tversky and Kahneman (1992) analyze the fourfold pattern of risk attitudes by plotting, for each positive prospect of the form $(x, p; 0, 1\text{-}p)$, the ratio of the certainty equivalent c of the prospect to the nonzero outcome x, c/x, as a function of p. We do the same in the negative domain, so we get two different graphs of c/x over p. Figure 7.8 provides these plots for the certainty equivalents provided by the average (idealized) participant.

FIGURE 7.8 – Risk attitudes of the average participant

	Q6	Q5	Q1	Q2	Q4	Q3
p	0.01	0.05	0.5	0.5	0.95	0.99
c/x	0.037	0.121	0.518	0.493	0.769	0.859
	risk seeking	risk seeking	risk seeking	risk averse	risk averse	risk averse

Q8	Q7	Q9	Q10	Q12	Q11
0.01	0.05	0.5	0.5	0.95	0.99
0.018	0.063	0.267	0.220	0.620	0.691
risk averse	risk averse	risk seeking	risk seeking	risk seeking	risk seeking



Source: Own elaboration

Should we estimate two smooth curves, one per domain, they would be interpreted as weighting functions assuming a linear value function. The fourfold pattern of risk attitudes in prospect theory predicts people tend to be risk seeking for gains of low probability (which we consider to be 1% and 5% in our test) and losses of medium and high probability, while we tend to be risk averse for gains of medium and high probability and losses of low probability. The pattern is clearly observable for the average respondent, with the nuance of an about risk neutrality for gains of medium probability. Results for the median respondent are quite similar.

Now, we may extend the analysis above to the individual level and obtain the results summarized in Table 7.11.[223] The risk attitudes predicted by prospect theory in the positive domain are generally satisfied, with about 2/3 of the elicitations being risk seeking for low probabilities and risk averse otherwise. In the negative domain the bias towards risk seeking is more evident, making results for low probabilities mixed.

TABLE 7.11 – The fourfold pattern at the individual level

	GAINS						LOSSES					
	low		medium - high				low		medium - high			
	p = .01	p = .05	p = .50	p = .50	p = .95	p = .99	p = .01	p = .05	p = .50	p = .50	p = .95	p = .99
risk seeking	63.5%	65.1%	30.2%	21.4%	0.0%	0.0%	47.6%	42.1%	84.1%	88.9%	89.7%	100%
risk neutral	10.3%	16.7%	34.1%	32.5%	15.9%	0.0%	14.3%	19.0%	11.9%	8.7%	10.3%	0.0%
risk averse	26.2%	18.3%	35.7%	46.0%	84.1%	100%	38.1%	38.1%	4.0%	8.7%	0.0%	0.0%

	GAINS		LOSSES	
	low	medium - high	low	medium - high
risk seeking	64.3%	12.9%	44.8%	90.7%
risk neutral	13.5%	20.6%	16.7%	7.7%
risk averse	22.2%	66.5%	38.1%	3.2%

Source: Own elaboration

Iteration and fitting errors

We determine the validity of participants' responses based on two kinds of errors. The first type, iteration errors, refers to the reliability of the iterative questions we asked to respondents to control for response errors. The second type, fitting errors, refers to those obtained in the non-linear regressions implemented for parameter estimation assuming the pre-specified parametric forms.

In regards to the iteration errors, Abdellaoui et al. (2008) argue that one of the main strengths of their model is that by allowing for response error during the elicitation process, the number of questions required to measure the value function is minimized. In particular, they repeated two types of iterations (see section 7.2 above) to obtain 96% reliability for the first replication and 66% for the second one, which they claim satisfactory. Using a similar approach, we repeated one iteration per question (with a somehow similar interpretation than Abdellaoui et al. (2008)'s second replication) for all twelve

[223] For risk-neutrality in Table 7.11 we report the percentage of elicitations that revealed a certainty equivalent that was the closest possible to the expected value of the game.

questions in the positive and negative domains. The results were highly satisfactory: on aggregate, only 5.6% of responses were contradictory (94.4% reliability). Furthermore, 65.4% of participants made not a single response error, 81.7% had one error at most, and only 2 out of 126 participants made more than three. These results confirm that the experiment design (graphics, instructions and practice questions) was helpful for participants to correctly understand the task. Whether some risk profiles are not 'regular ones' (as it happens for instance with α^- and γ^- estimations noted above) might hence be attributed to the difficulties for some participants to imagine hypothetical losses as real, but not to a misinterpretation of data.

In what fitting errors is referred, the high quality of the R^2 coefficients obtained to estimate the PT parameters for most individuals are both an additional confirmation that participants understood the task, as well as an indicative that the parametric specifications and scaling method we used were satisfactory. In addition, for those respondents whose coefficients were low, this in most cases might only indicate that with other value and weighting functions the fit quality would improve. Nonetheless, in section 'anomalies at the individual level' below we analyze some results at the individual level that are difficult to rationalize and that might reveal some mistakes or confusion by the respondent. In such case we will discuss whether they should be removed from data or not. Table 7.12 summarizes the R^2 coefficients obtained.

TABLE 7.12 – Coefficients of determination

	positive domain	**negative domain**
$R^2 \geq 99$	19.8%	19.0%
$R^2 \geq 90$	79.4%	65.1%
$R^2 < 50$	2.4%	0.8%

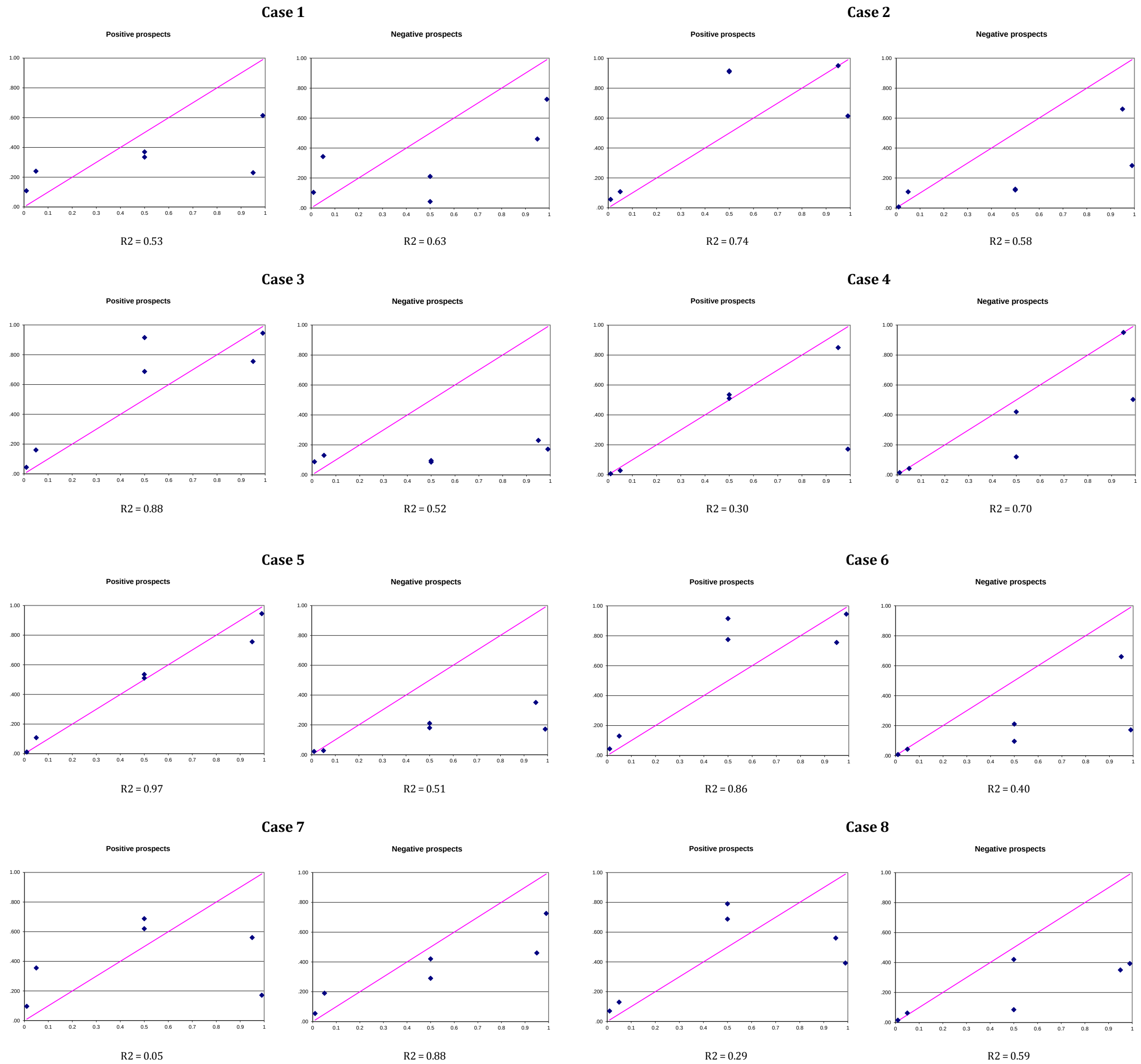
Source: Own elaboration

We may see that results are slightly better in the positive domain, with about 80% and 65% of the individual regressions being satisfactory and only three observations (2.4%) in the positive domain and one (0.8%) in the negative domain being really weak.

Anomalies at the individual level

The coefficients of determination R^2 are helpful to identify some results at the individual level that are difficult to put in consonance with the basic predictions of prospect theory. We highlight eight cases whose risk attitudes (plotting of c/x over p) are described in Figure 7.9 next. These individuals show the lowest fitting accuracy either on any of the two domains of both. As an additional piece of evidence, all but one of these individuals made at least one iteration error, for an average of 1.75 errors per respondent, statistically higher ($p < 0.01$) than 0.61 of all the other participants, which might suggest these profiles correspond to participants that had more problems to understand the task.

FIGURE 7.9 – Risk attitudes of eight individual anomalies



Source: Own elaboration

In some cases it seems difficult not to agree that some answers reveal a response error. Just to illustrate, p = 0.99 in the positive domain of case 4 or the same probability in the negative domain of case 6. Other examples reveal profiles that are hard to rationalize. Take for instance case 7 in the positive domain (the one with the lowest coefficient of determination of all participants, $R^2 = 0.05$), where the respondent required 355 euros for not accepting a prospect to win 1,000 euros with 5% probability, but a lower amount (342.5 euros) for not accepting 2,000 euros with 95% probability. Similar situations appear when comparing responses for p = 50% with high and low probabilities (e.g., case 1 in the negative domain or 8 in the positive one).

However, other cases show a risk profile that is too aggressive or unusual, but not necessarily a response error. Take for instance case 3 in the negative domain, which features a high risk seeking profile, or cases 2 and 6 in the positive domain, which might reveal that the inverse-S shaped weighting function is not suitable for them. Hence, we conclude we cannot detect anomalies based solely on R^2. Furthermore, removing some of these individuals on a case by case basis might be misleading, for two reasons. First, though we believe our reasons are well grounded, some may say it introduces a subjective criteria by the experimenter. Second, there may be other anomalies that are not so evident in terms of a low R^2 value, what would require analyzing the whole experimental group on a case by case basis.

Henceforth, given the conclusions of our analysis at the individual level we decide not to remove any observations for any of the PT parameters. However, we think lessons can be learned for future research. Some improvements can be made to our tests that do not affect its goodness of fit. The idea is to ask only six questions per domain as option-by-default, but setting the computer application to ask additional questions when an individual provides an answer that might be interpreted as a response error. Two examples of answers that would trigger a check question could be some pairs of questions[224] that are given responses which are different up to pre-specified levels, and *c/x* ratios for questions with probabilities p = 0.5 that are below (above) ratios at low (high) probabilities. This scheme would be helpful to confirm answers that discard response errors, while it only requires additional questions (and time to complete the tests) to some participants.

We leave two open questions in search for additional improvements that can be made to our tests. First, regarding loss aversion, we made three questions to estimate β_{med} and β_{avg} under the assumption that utility is linear for small amounts of money. Both measures lose information when estimations are made from only three questions, but median estimations worked better. This is attributed, in most cases, to the evidence that answers to the higher amount (100 euros) tend to be affected by the curvature of the value function.[225] One might suggest that posing three questions with values like 1, 5 and 10 euros, or 1, 10 and 20, might be a better option to assume linearity of the utility function. However, we should be careful as the sensibility of the value function to higher or lower amounts of money varies across individuals. For instance, samples of older individuals or with higher income levels might reveal insensitivity to such low amounts of money —hence eliciting loss aversion levels that are closer to 1.

A second open question is in regard to how to foster more realistic answers by participants in the experiment. This problem is universal in experimental economics, where we require participants taking roles *on bona fide* but in hypothetical situations. A classic solution is to implement a set of incentives.

---

224 In our tests the pairs of questions would be both questions for p = 0.5, questions for p = 0.01 and p = 0.05, and questions for p = 0.95 and p = 0.99.

225 Table A5 in the Appendix shows median answers to questions with 1 euro and 10 euros exhibit a loss aversion of 2.0, but with 100 euros it increases to 3.0. If we compare average answers, loss aversion increases but the effect is observed anyway: 3.0 for 1 and 10 euros, but 4.85 for 100 euros. We could also estimate a truncated average at 5% to exclude extreme values from average estimations to get the same effect: 2.6 and 2.8 for 1 euro and 10 euros, but 3.9 for 100 euros.

However, we observed this unrealistic behavior particularly in the negative domain, where participants are exposed to potential losses. In this scenario, the incentive solution is implausible as it would require a sample of individuals willing to participate in an experiment where they are offered to lose real money.

7.4. HYPOTHESIS TESTING AND RESULTS

7.4.1. Hypotheses

Once the validity of the questionnaires has been confirmed, we now use the estimated parameters to test two types of hypotheses: the effect of priors over variables, and the relationship among variables. We leave the second type to the end of this section. Regarding the first effect, we review the literature to posit several hypotheses regarding the effects of priors over the variables in our tests.

Gender. Lundeberg, Fox and Punccohar (1994) show men are more overconfident. Barber and Odean (2001) show men trade more frequently and exhibit more losses than women, and attribute it to male overconfidence. Kamas and Preston (2012) investigate whether gender differences in choosing to enter competitive tournaments are due to women's lower taste for competition or differences in confidence, with mixed results. Kuyper and Dijkstra (2009) examine the better-than-average effect among secondary school students during 3 consecutive years and find strong support on the hypothesis that boys exhibit more overplacement than girls. Following this research, we set the next hypothesis:

Hypothesis 1

H0: Men are more overconfident than women

1a – H0: Men are more overconfident in terms of overestimation (higher E)

1b – H0: Men are more overconfident in terms of overplacement (higher P)

1c – H0: Men are more overconfident in terms of overprecision (lower M)

Schmidt and Traub (2002) find female subjects exhibit both a more frequent occurrence and a larger extent of loss aversion. Booij et al. (2010) find females are more risk averse than males due to probability weighting and loss aversion. On the contrary, Abdellaoui et al. (2008) find no gender effect on loss aversion. Hence, we suggest the next hypothesis:

Hypothesis 2

H0: Women exhibit a larger degree of loss aversion than men

2a – H0: Women exhibit a higher β_{med}

2b – H0: Women exhibit a higher β_{avg}

Booij et al. (2010) find the weighting function for gains varies with gender and age, while for losses it seems unrelated to any background variables. Contrariwise to earlier studies that ascribed the higher risk aversion of women solely to differences in the degree of utility curvature, their results show this gender difference is driven by probability weighting and loss aversion. Abdellaoui et al. (2008) also find no significant gender-dependent difference in utility curvature for either gains or losses. Hence, we want to test which parameters explain the higher risk aversion observed for women, either the curvature of the utility (α^+ and α^-) or the weighting (γ^+ and γ^-) functions. The first case is easy to test, simply stating the following hypothesis:

Hypothesis 3

H0: Women are more risk averse in terms of utility curvature

3a – H0: Women exhibit lower α^+

3b – H0: Women exhibit higher α^-

It is important to note once again that, here and in section results, whenever we say something like "women are more risk averse in terms of alpha", we are ignoring the effect of probability weightings. Indeed, the fourfold pattern of risk attitudes requires to discuss risk aversion and risk seeking in terms of value and weighting functions simultaneously.

The second case, that is, the hypothesis that risk aversion is explained by the curvature of the weighting function, must be qualified. Given the properties of one-parameter weighting functions like Prelec-I, the lower γ^+ (the higher γ^-) the higher risk aversion, but only for gains (losses) of moderate to high probability. For gains and losses of low probability, the risk profile is the opposite. Consequently, we test the following:

Hypothesis 4

H0: Women are more risk averse in terms of curvature of the weighting function

4a – H0: Women exhibit lower γ^+ (for gains of moderate/high probability only)

4b – H0: Women exhibit higher γ^- (for gains of moderate/high probability only)

Age. Regarding the effects of age on overconfidence, results are mixed. Crawford and Stankov (1996) review the literature to find a tendency of greater caution with increasing age, such that the older the person the lower the overconfidence. However, it is also widely accepted that most abilities spanned by typical tests of mental ability show a decline with increasing age through adulthood. The general finding is that working on recall prediction tasks *"there is a fairly consistent tendency for older adults to show greater overconfidence in their performance predictions"* (p. 89). Other authors supporting the idea that overconfidence increases with age include Hanson et al. (2008) in intuitive confidence intervals (i.e., overprecision), though it may be compensated by an age-related increase in knowledge.

On the contrary, Sandroni and Squintani (2009) find young adults (18 to 24 years old) are less likely than any other risk class to buy health or motorist insurance, and assert that established experimental evidence finds overconfidence is particularly pervasive among young adults. Zell and Alicke (2011) also investigated whether overplacement is related to age, finding a better-than-average effect in people of all ages, but particularly relevant for young and middle-aged adults on dimensions for which older people have clear deficiencies (i.e., athleticism, physical attractiveness). Finally, Grinblatt and Keloharju (2009) don't find consistent results to suggest age is able to explain the higher trading of overconfident traders, nor the gender gap in trading between men and women. Hence, we choose to shed some light on this debate by testing the following hypothesis:

Hypothesis 5

H0: The younger the person, the more overconfident he/she is

5a – H0: The younger, the higher the overestimation (higher E).

5b – H0: The younger, the higher the overplacement (higher P)

5c – H0: The younger, the higher the overprecision (lower M)

Education. Booij et al. (2010) find education —defined as having a higher academic degree— does not affect utility curvature, nor it is associated with a more linear weighting of probabilities. They find this result surprising: if we view expected utility as the rational choice of model under risk, one would expect higher educated individuals to weight probabilities more linearly. However, they do find education to be associated with a lower degree of loss aversion, suggesting that the reduction in risk aversion with years of schooling observed in empirical research (e.g., Donkers et al., 2001) stems mainly from lower sensitivity to losses. Hence, we want to check two hypotheses…

Hypothesis 6

H0: The higher the education (academic degree), the more linear probability weighting

6a – H0: The higher the education, γ^{+} closer to 1

6b – H0: The higher the education, γ^{-} closer to 1

Hypothesis 7

H0: The higher the education (academic degree), the lower the degree of loss aversion

7a – H0: The more education, the lower loss aversion (lower β_{med})

7b – H0: The more education, the lower loss aversion (lower β_{avg})

…plus one additional hypothesis in terms of academic experience having a positive effect over subjects' ability to be more objective in terms of overconfidence.

Experience. We interpret working experience in the same sense as education. Thus, we interpret experience could have a positive effect over subjects' ability to be more objective in their estimations learning how to weight probabilities more linearly, and moderating both under- and overconfidence. Hence we want to test three sets of hypotheses:

Hypothesis 8

H0: The more experience the more linear probability weighting

8a – H0: The more experience, γ^+ closer to 1 (higher γ^+)

8b – H0: The more experience, γ^- closer to 1 (higher γ^-)

Hypothesis 9

H0: The more experience, the lower the degree of loss aversion

9a – H0: The more experience, the lower loss aversion (lower β_{med})

9b – H0: The more experience, the lower loss aversion (lower β_{avg})

Hypothesis 10

H0: The more experience, the more objective estimations in terms of confidence

10a – H0: ... $|E|$ in absolute terms is closer to 0.

10b – H0: ... $|P|$ in absolute terms is closer to 0.

10c – H0: ... $|M|$ in absolute terms is closer to 1.

Skills (in finance)**.** Most participants are students of some degree related to finance (business and economics). However, we included a subgroup of students in computing, law and others, what allows us to test the effects of financial skills over risk attitudes and overconfidence. In particular, we want to test the following hypotheses:

Hypothesis 11

H0: Skills in finance reduce overconfidence

11a – H0: Skills in finance reduce overestimation (lower E).

11b – H0: Skills in finance reduce overplacement (lower P)

11c – H0: Skills in finance reduce overprecision (higher M)

Hypothesis 12

H0: Skills in finance increase loss aversion

12a – H0: Skills in finance exhibit a higher β_{med}

12b – H0: Skills in finance exhibit a higher β_{avg}

Hypothesis 13

H0: Skills in finance increase risk aversion

13a – H0: Skills in finance exhibit a lower α^+

13b – H0: Skills in finance exhibit a higher α^-

Hypothesis 14

H0: Skills in finance induce a more linear probability weighting

14a – H0: Skills in finance exhibit a higher γ^+

14b – H0: Skills in finance exhibit a higher γ^-

A second set of hypotheses may be posed to test the relationship among the behavioral variables, rather than the effect of priors over the variables. For instance, as we saw in Section 7.2, a classic result is that overprecision is more persistent than the other two types of overconfidence (Moore and Healy, 2008), though its presence reduces the magnitude of both overestimation and overplacement. Consequently, we are interested in testing the following hypothesis:

Hypothesis 15

H0: The higher the overprecision the lower overestimation and overplacement

15a – H0: The lower M, the lower E

15b – H0: The lower M, the lower P

Additional hypotheses could be posed by an exploratory analysis of correlations among overconfidence and PT parameters to see, for instance, if more risk seeking individuals are correlated with those that are more overconfident.

7.4.2. Results

We conduct an analysis at the variable level and a factorial analysis. We analyze them separately.

Variable analysis

First thing to note is that three priors are strongly correlated: age, level (education) and (working) experience. Table 7.13 summarizes the correlations and statistical significance. Correlations with age hardly vary when outliers are excluded, denoted age (r) in the table. These correlations may affect the results in the hypothesis testing, particularly when using regressions —as multicollinearity might appear. In addition, a generic way to set the hypothesis testing is to obtain the correlation matrix among priors and behavioral variables. Table 7.14 summarizes the results we obtain. The only significant correlation between priors and variables appears between level (education) and loss aversion (β_{med} at barely 5%, β_{avg} for $p < 0.05$), but with a positive sign (rejecting the null hypothesis in test 7a). Despite these results, remember we declared level in our experimental group to be a bad proxy for education, so we would take the interpretation that education increases loss aversion only carefully.[226]

[226] Some other relationships between priors and variables go in the same direction as the null hypotheses tested, but with no statistical significance. First, age reduces overconfidence: older students exhibit lower overestimation and overplacement (with no statistical significance) as well as of overprecision, with a statistical significance that improves for both measures, but only to about 20%. Second, educated (level) and more experienced individuals (working experience) weight probabilities more linearly, but only in the positive domain (γ^+). Third, working experience reduces both measures of loss aversion.

TABLE 7.13 – Correlations among priors

Correlations

		Age (r)	Level	Exper.
Age (r)	Pearson Correlation	1	,616**	,403**
	Sig. (2-tailed)		.000	.000
	N	125	125	125
Level	Pearson Correlation	,616**	1	,210*
	Sig. (2-tailed)	.000		.018
	N	125	126	126
Experience	Pearson Correlation	,403**	,210*	1
	Sig. (2-tailed)	.000	.018	
	N	125	126	126

Correlations

		Age	Level	Exper.
Age	Pearson Correlation	1	,497**	,409**
	Sig. (2-tailed)		.000	.000
	N	126	126	125

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own elaboration

TABLE 7.14 – Correlation matrix. Priors and variables

Correlations

		Age (r)	Level	Exper.	E	P	Mmed	Mavg	alpha +	alpha -	gamma +	gamma -	βmed	βavg (r)
Age (r)	Pearson Correlation	1	,616**	,403**	-.030	-.065	.111	.114	.070	.033	.056	-.035	.042	.090
	Sig. (2-tailed)		.000	.000	.738	.474	.221	.208	.439	.714	.532	.699	.643	.324
	N	125	125	125	125	125	124	124	125	125	125	125	125	122
Level	Pearson Correlation	,616**	1	,210*	-.024	.047	-.027	.041	-.001	-.029	.018	-.054	.174	,209*
	Sig. (2-tailed)	.000		.018	.790	.598	.764	.647	.987	.746	.842	.551	.051	.020
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
Experience	Pearson Correlation	,403**	,210*	1	.151	.046	.035	-.060	.077	-.094	.054	-.105	-.036	-.002
	Sig. (2-tailed)	.000	.018		.091	.611	.700	.508	.394	.294	.548	.244	.690	.980
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
E	Pearson Correlation	-.030	-.024	.151	1	,690**	-.123	-.166	-.055	.165	.055	-.025	-.065	-,199*
	Sig. (2-tailed)	.738	.790	.091		.000	.173	.064	.544	.065	.537	.782	.468	.027
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
P	Pearson Correlation	-.065	.047	.046	,690**	1	-.039	-.144	-.122	.096	.104	.069	-.010	-.089
	Sig. (2-tailed)	.474	.598	.611	.000		.664	.109	.174	.285	.246	.441	.913	.325
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
Mmed	Pearson Correlation	.111	-.027	.035	-.123	-.039	1	,672**	-.121	.008	.032	.165	.052	.087
	Sig. (2-tailed)	.221	.764	.700	.173	.664		.000	.180	.932	.723	.066	.564	.339
	N	124	125	125	125	125	125	125	125	125	125	125	125	122
Mavg	Pearson Correlation	.114	.041	-.060	-.166	-.144	,672**	1	-.095	.041	-.021	.144	.122	,193*
	Sig. (2-tailed)	.208	.647	.508	.064	.109	.000		.293	.653	.812	.110	.175	.033
	N	124	125	125	125	125	125	125	125	125	125	125	125	122
alpha +	Pearson Correlation	.070	-.001	.077	-.055	-.122	-.121	-.095	1	-,211*	,597**	-.133	-.036	-.040
	Sig. (2-tailed)	.439	.987	.394	.544	.174	.180	.293		.018	.000	.139	.687	.658
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
alpha -	Pearson Correlation	.033	-.029	-.094	.165	.096	.008	.041	-,211*	1	-.093	,326**	,294**	,308**
	Sig. (2-tailed)	.714	.746	.294	.065	.285	.932	.653	.018		.301	.000	.001	.001
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
gamma +	Pearson Correlation	.056	.018	.054	.055	.104	.032	-.021	,597**	-.093	1	,250**	-.068	-.097
	Sig. (2-tailed)	.532	.842	.548	.537	.246	.723	.812	.000	.301		.005	.450	.287
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
gamma -	Pearson Correlation	-.035	-.054	-.105	-.025	.069	.165	.144	-.133	,326**	,250**	1	-.035	.008
	Sig. (2-tailed)	.699	.551	.244	.782	.441	.066	.110	.139	.000	.005		.698	.926
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
βmed	Pearson Correlation	.042	.174	-.036	-.065	-.010	.052	.122	-.036	,294**	-.068	-.035	1	,918**
	Sig. (2-tailed)	.643	.051	.690	.468	.913	.564	.175	.687	.001	.450	.698		.000
	N	125	126	126	126	126	125	125	126	126	126	126	126	123
βavg (r)	Pearson Correlation	.090	,209*	-.002	-,199*	-.089	.087	,193*	-.040	,308**	-.097	.008	,918**	1
	Sig. (2-tailed)	.324	.020	.980	.027	.325	.339	.033	.658	.001	.287	.926	.000	
	N	122	123	123	123	123	122	122	123	123	123	123	123	123

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own elaboration

In regards to the statistical correlation among behavioral biases, more significant results appear. First, there is clear evidence that overestimation and overplacement are highly correlated ($p < 0.01$). However, our results don't support Moore and Healy (2008)'s assertion that overprecision reduces both overestimation and overplacement. On the contrary, it increases both E and P, though the correlations are only barely significant for M_{avg}. A second set of correlations may be traced among PT parameters. We find very interesting results. First, risk seeking comes together in both domains: α^{+} and α^{-} are correlated (note the negative sign) with statistical significance ($p < 0.05$). Second, an objective weighting of probabilities also come together in both domains: γ^{+} and γ^{-} are positively correlated with high statistical significance ($p < 0.01$). Additionally, α^{+} and γ^{+} as well as α^{-} and γ^{-} are correlated with high significance ($p < 0.01$), but this may be only a result of both pairs of parameters being estimated simultaneously. Finally, there is strong evidence that loss aversion and risk aversion in the negative domain come together as well. We must be careful with this result, as we noted in subsection 7.3.2 that our measures of loss aversion (particularly β_{avg}) may be affected by utility curvature. However, two facts support the reliability of this correlation. First, the median indicator shows the best results. Second, the positive relationship between α^{-} and β_{avg} works better when outliers are excluded ($p < 0.01$).

Finally, we may observe the relationship between OC and PT parameters. We find only significant positive correlations (at 10%) between α^{-} and E and between γ^{-} and M. These correlations are harder to interpret, as they suggest individuals with a more aggressive profile for losses (higher risk seeking and distortion of probabilities) would be correlated with lower levels of overconfidence (in terms of overestimation and overprecision). However, this result might also be consistent with Kahneman and Lovallo's (1993) suggestion that biases can cancel out.

Some hypotheses require alternative testing solutions other than correlations. These include tests for gender and skills, which are nominal variables, and the Hypothesis 10, which requires an alternative procedure. In the first case, we implement an ANOVA test (difference of means test). Results are summarized in Table A.9 in the Appendix. Regarding gender, significant differences ($p < 0.05$) appear in terms of M_{avg}, α^{+}, α^{-} and γ^{-}, and in terms of M_{med} ($p < 0.1$). This implies women are significantly more overconfident than men in terms of overprecision (contrary to Hypothesis 1), more risk seeking in terms of utility curvature both in the positive and negative domains (contrary to Hypothesis 3) and with a higher distortion of probabilities in the negative domain. Regarding skills, the results obtained suggest skills in finance increases objectivity reducing probability distortion ($p < 0.01$) and reduces risk aversion ($p < 0.1$), both in the positive domain. The first result supports Hypothesis 14, the second one goes against Hypothesis 13.[227]

[227] Several other relationships go in the same direction as the null hypotheses to be tested, but with no statistical significance at all. Regarding gender these include men are more overconfident in terms of M and P, while women are more risk seeking (both domains) in terms of utility curvature but more loss averse. Regarding skills in finance, these include reducing overestimation and increasing loss aversion (β_{med}).

In the second case, Table 7.15 summarizes the correlations between level and experience on one hand, and the absolute deviations of the OC measures with respect to neutrality (i.e., the absolute values of E and P, and the absolute deviations of M with respect to 1).[228] Contrary to our hypotheses, we obtain significant evidence that experience reduces objectivity in terms of estimation of self-performance.

TABLE 7.15 – Correlation matrix for objectivity

Correlations

		Level	Exper.	Eabs	Pabs	Mabs
Level	Pearson Correlation	1	,210*	-0.0334	-.083	-.027
	Sig. (2-tailed)		.018	.710	.353	.764
	N	126	126	126	126	125
Experience	Pearson Correlation	,210*	1	,222*	.136	.035
	Sig. (2-tailed)	.018		.012	.130	.700
	N	126	126	126	126	125
Eabs	Pearson Correlation	-0.03	,222*	1	-.023	-.144
	Sig. (2-tailed)	.710	.012		.799	.108
	N	126	126	126	126	125
Pabs	Pearson Correlation	-.083	.136	-.023	1	.169
	Sig. (2-tailed)	.353	.130	.799		.060
	N	126	126	126	126	125
Mabs	Pearson Correlation	.052	-.029	.118	-,198*	1
	Sig. (2-tailed)	.562	.751	.190	.027	
	N	125	125	125	125	125

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own elaboration

Finally, we conduct a regression analysis of behavioral biases over priors, where gender and skills are dummy variables.[229] Since multicollineality appears among age, level and experience we perform a stepwise procedure for variable selection. Results are summarized in Table 7.16. More complete information about the regressions is available in Table A.10 in the Appendix.

TABLE 7.16 – Regression models. Behavioral biases to priors

	Model					
	1	2	3	4	5	6
Dependent variable	M_{avg}	α^+	α^-	γ^+	γ^-	β_{avg}
Constant	0.406	1.127	0.463	0.504	0.468	2.429
Gender	0.108	-0.197	0.111	-	0.109	-
(signific.)	0.039	0.016	0.045		0.027	
Age	-	-	-	-	-	-
(signific.)						
Level	-	-	-	-	-	0.186
(signific.)						0.020
Skills	-	-	-	0.167	-	-
(signific.)				0.005		
Experience	-	-	-	-	-	-
(signific.)						
R^2	0.034	0.046	0.032	0.062	0.039	0.044
adj. R^2	0.026	0.038	0.024	0.054	0.031	0.036

Source: Own elaboration

[228] For simplicity we report only *M* in absolute terms using M_{med} observations.
[229] Dummy variables were defined as (0 = woman; 1 = man) for gender and (0 = other skills; 1 = skills in finance) for skills.

We obtain results that are coherent with the correlations above. In particular, they predict women exhibit more overprecision (lower M_{avg}), higher risk seeking in terms of utility curvature (higher α^+ and lower α^-) and higher distortion of probabilities in the negative domain (lower γ^-). Skills in finance would explain a more objective weighting of probabilities (higher γ^+) while the more education (level) the higher loss aversion (β_{avg}). The explanatory power of these models is very low in all instances, but significantly different from zero in any case.

Factorial analysis

We conduct a factor analysis of overconfidence measures on one hand, and prospect theory on the other.[230] Results are summarized in Table 7.17.

TABLE 7.17 – Factorial analysis. Overconfidence and PT

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.497
Bartlett's Test of Sphericity	Approx. Chi-Sq	82.247
	df	3
	Sig.	.000

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.424
Bartlett's Test of Sphericity	Approx. Chi-Sq	112.082
	df	10
	Sig.	.000

Component Matrix[a]

	Component
	1
Overestimation	.919
Overplacement	.907
Overprecision M_{med}	-.208

Extraction Method: Principal Component Analysis
a. 1 components extracted.

Rotated Component Matrix[a]

	Component		
	1	2	3
gamma +	.891	.246	-.086
alpha +	.888	-.229	.013
gamma -	.082	.922	-.090
alpha -	-.199	.608	.559
β_{med}	.011	-.065	.933

Extraction Method: Principal Component Analysis
Rotation Method. Varimax Normalization with Kaiser.[a]
a. Rotation converged in 4 iterations.

Source: Own elaboration

We may observe that the Principal Component Analysis (PCA) provides quite intuitive results. On one hand, it suggests all overconfidence variables may be synthetized into a single factor, which from now on we denote as **OC**. The sign of each bias is coherent with their interpretation: *E* and *P* are positively related to overconfidence, while *M* is negatively related to it. Prospect theory parameters, on the other hand, are assembled into three factors that separate the risk profile for gains, the risk profile for losses, and loss aversion. The rotated component matrix suggests the first factor would correspond to the risk profile for gains (α^+ and γ^+), hence we will denote it **GAINS**. Both variables load positively on this factor, implying the higher the GAINS factor the more risk seeking.[231] The second factor would symmetrically correspond to the risk profile for losses (α^- and γ^-), which we denote **LOSSES**. Since both variables load positively on it, now this factor should be interpreted as higher LOSSES implying

[230] For simplicity, for overprecision and loss aversion in the factorial analysis we have only considered the median measures, M_{med} and β_{med} respectively.
[231] Note that higher γ^+ implies more risk seeking only for medium/high probabilities.

more risk aversion (again, higher γ^- implies more risk aversion only for medium/high probabilities). Finally, the third factor basically corresponds to loss aversion (β_{med}) with some additional effect by risk aversion to losses (α^-). Both variables load positively on this factor, suggesting that the higher loss aversion (and risk aversion to sure losses), the higher the factor. Hence, we denote this factor **LOSSAVERSION**.

We may reproduce similar analyses based on ANOVA tests and regressions as we did before, but now using factors instead of behavioral variables. The ANOVA tests for gender and skills —summarized in Table A.11 in the Appendix— provide additional support on the hypotheses that women exhibit a higher aversion to a sure loss (a risk seeking profile since LOSSES is significantly lower for them than for men) and that skills in finance reduces risk aversion in the positive domain (GAINS). Finally, regression results provide identical support to both findings, summarized in Table 7.18.

TABLE 7.18 – Regression models. Behavioral factors to priors

	Model 1	Model 2
Dependent variable	**GAINS**	**LOSSES**
Constant	-0.489	-0.283
Gender	-	0.540
(signific.)		0.002
Age	-	-
(signific.)		
Level	-	-
(signific.)		
Skills	0.593	-
(signific.)	0.011	
Experience	-	-
(signific.)		
R^2	0.051	0.073
adj. R^2	0.043	0.066

Source: Own elaboration

7.5. CONCLUSIONS

We introduced a set of tests to elicit the three measures of overconfidence as well as the complete set of parameters of value and weighting functions in prospect theory. We also provide extensive evidence that the experimental research implemented to validate our tests confirm they are broadly efficient to replicate the standard results in the literature. In particular, the results obtained are in order.

First, with only four trivia similar to those by Moore and Healy (2008) we obtain satisfactory results in terms of simplicity (it requires only about 8 minutes per indicator) and efficiency to provide individual measures of overestimation and overplacement.

Second, a test of fifteen questions in about 20 minutes revealed effective as well to replicate the main findings of prospect theory, considering the properties of the value and weighting functions, the fourfold pattern of risk attitudes, iteration and fitting errors, and anomalies at the individual level.

Third, our test for overprecision, instead, revealed to be unable to obtain individual estimations that are stable for different refinement methods. In future research, having more questions per domain will be necessary, while it would also be desirable to ask additional questions on personal experience to balance domains.

Fourth, the chapter also contributes to provide additional evidence about how gender, education and skills in finance affect overconfidence and risk aversion. In particular, our analysis enhances the scope for empirical application of prospect theory and overconfidence by using the same group of respondents in the experimental analysis —something that, to the best of our knowledge, was not done before. This allows us to provide new insight on the relationship between these two relevant areas in the behavioral literature.

Additional enhancements for future research might be introducing questions on abilities and perceptual tasks (Stankov et al., 2012) in the trivia test to moderate the general drift towards overestimation, and setting the computer application in the PT test to refine answers that might be interpreted as a response error by asking an additional questions. Finally, two open questions in the PT test are how to improve loss aversion estimations, since sensibility of the value function to lower amounts of money varies across individuals, and how to foster more realistic answers, particularly in the negative domain as incentives would be an implausible solution as it would require a sample of individuals willing to participate in an experiment where they are offered to lose real money.

CHAPTER 8. CREDIT POLICIES IN AN EXPERIMENTAL SETTING

8.1. OBJECTIVE

We continue the experimental research in Chapter 7 to determine whether the behavioral biases identified among a series of participants in the experiment could feed, among that same set of respondents, a risk-seeking behavior in a simulated credit market. We design an original business simulation game and organized a series of five experimental sessions with students described in Chapter 7 to test the effects that different levels of overconfidence and risk profile according to prospect theory have on the credit policies the participants implemented in the experiment. Thus, in Chapter 8 we describe how the experimental game was designed and the results that were obtained.[232]

Following the outline described in Figure 7.1, in Chapter 7 we obtain a behavioral profile of each participant in the experiment. Now, Chapter 8 deals with the right-hand side of that outline: the design of a strategy game that replicates how banks grant credit to customers, in order to obtain information about how much credit and at what price different subjects would grant, under conditions of uncertainty and risk about the economic environment. In short, the game is designed to obtain specific information about how different players (the same 126 participants that completed the behavioral tests in Chapter 7) behave when granting credit to the economy, in order to test the possible relationships between behavioral profile and risk attitudes in the game.

In what follows we explain how the experiment was implemented in two instances. In Section 8.2 we explain the design of the experiment: we briefly review the literature on business simulation games and recall our discussion on banking efficiency and credit markets in Chapter 1 to propose a set of dependent variables, representative of the credit policies, to be tested against the behavioral profiles of the respondents. Then, in Section 8.3 we explain how the experiment was conducted; instructions given to participants and procedures they were told to implement in order to set their optimal credit policies.

The chapter is organized as follows. First, in Section 8.2 we explain the experiment design. Section 8.3 describes the basics of the game and variables to be measured. Section 8.4 analyzes the data matrix that resulted. Section 8.5 provides the hypotheses to be tested and the results we obtain. Finally, Section 8.6 concludes.

[232] The remainder of this Chapter 8 reproduces a manuscript in the third round of revision in a JCR ranked journal at the time of the writing of this thesis.

8.2. EXPERIMENT DESIGN

Our goal is to implement an experimental design that sets participants in a situation where they play the role of a bank having to grant credit to a series of customers, provided a set of information about clients' solvency and macroeconomic perspectives. With that goal in mind, in this section we make a short review of the literature on business simulation games, banking efficiency and credit markets. This will lead us to define the basic approach to the game design, as well as the variables representative of the credit policies by participants in the experiment we want to test.

8.2.1. Literature on business simulation games

Experimental economics —the use of experimentation to address economic questions (Loewenstein, 1999)— is a growing field. Controlled laboratory experimentation came to help economists to solve a major empirical challenge: going beyond correlational analysis to provide insights on causation (List, 2009). Furthermore, since the experimental model of the physical sciences revealed a good method to understand human behavior (Levitt and List, 2009), the success of the experimental approach is particularly relevant in behavioral economics. A brief review of literature on experimental economics and, in particular, on business simulation games, will be essential to describe the type of research we are about to conduct and the main characteristics it must incorporate.

Harrison and List (2004) define what might be better called an ideal experiment: the one that *"is able to observe a subject in a controlled setting but where the subject does not perceive any of the controls as being unnatural and there is no deception being practiced."* They consequently classify controlled experiments in laboratory and field experiments —the latter being either artefactual, framed or natural.[233] Framed field experiments have the advantage of avoiding some shortcomings of social experiments such as randomization bias, attrition bias and substitution bias (Levitt and List, 2009).[234] However, a classic problem is in regards of their external validity:[235] the fact that subjects are in an environment where they are aware that their behavior is being monitored, recorded, and subsequently scrutinized, might cause generalizability to be compromised (Levitt and List, 2007). The incorporation

[233] We may recall our description of controlled experiments, provided in Chapter 2. Thus, artefactual field experiment is the most minor departure from the typical laboratory experiment, in the sense that it mimics a lab experiment except that it uses 'non-standard' subjects. A framed field experiment would be the same as an artefactual field experiment, except that it incorporates important elements of the context of the naturally occurring environment. Finally, natural experiments are those completed in cases where the environment is such that the subjects naturally undertake these tasks and where they do not know they are participants in an experiment. (Harrison and List, 2004; Levitt and List, 2009).

[234] Experimental research involves the generation of a random sequence by which to assign subjects: the randomization sequence must be adequately protected so subjects are not aware of the upcoming assignment (Viera and Bangdiwala, 2007). Attrition is a type of selection bias caused by loss of participants, due either to missing data or dropouts (Graham, 2009).

[235] Most empirical research by psychologists discuss the tension of internal and external validity. Internal validity refers to the ability to draw confident causal conclusions from one's research. External validity refers to the ability to generalize from the research context to the settings that the research is intended to approximate (Loewenstein, 1999).

of markets, repetition and incentives would improve their validity, but perhaps not completely solve the problem.[236] Consequently, we will discuss the external validity of our experiment in the conclusions to this chapter.

Lab and field experiments have been used to test a wide variety of economic issues, including auction, the private provision of public goods, preference elicitation, competitive market theory, and information assimilation among traders (see Levitt and List, 2009, for further details). Our experiment is designed to explore retail credit markets in terms of the last genre, i.e., informational assimilation. In particular, we conduct a simulation of a retail credit market for such purpose.

A simulation is an evolving case study of a particular social or physical reality in which the participants take *on bona fide* roles with well-defined responsibilities and constraints (De Freitas and Oliver, 2006; Gredler, 2004). Three basic elements any experiment in economics must incorporate are an environment defining the payoffs, an institution defining the language and rules, and behavior (Smith, 2001). More specifically, Gredler (2004) defines four important characteristics of simulations: (i) a model that permits the students to interact with a complex real-world situation; (ii) a defined task and role for every participant involved; (iii) an environment that allows students to execute a range of strategies; and (iv) the presence of a feedback system for participants in order to create a change of strategies in them.

To sum up, for our experimental setting to be satisfactory two types of elements must be correctly addressed. First, the four characteristics of simulations outlined above must be considered. Second, the definition of performance indicators must be specified. In particular, these indicators must be able to synthetize the relevant results in this simulated retail credit market that we want to test against the participants' behavioral profile. To this purpose is devoted the literature review in subsection 8.2.2 next.

8.2.2. Searching for performance indicators in our game

Our main concern is to design a strategy game that helps us to identify how different players would behave in a retail credit market. The key point is to obtain a set of indicators, meant to be the dependent variables in the experiment, that are in accordance with what academic literature says about how credit markets operate and banking efficiency. We recall here the review of literature we made on these two topics in Chapter 1.

Regarding the literature on credit markets, two broad views on what determines how much private credit a financial system would extend (Djankov, McLiesh and Shleifer, 2005) are the power theories and the information theories of credit. The informational approach is closer to the scope of our analysis in the experiment. In short, this view of credit markets considers it essential to estimate the

[236] Loewenstein (1999) considers that *"despite their incorporation of markets, repetition and incentives, EEs have not, in my opinion, been able to avoid the problem of low external validity that is the Achilles heel of all laboratory experimentation."*

ability of borrowers to repay their debts (which depends on the expected future income of their assets and collateral pledged), and consequently the ability of lenders to screen good borrowers from bad borrowers, in order to implement the credit policies that maximize their profits adjusted by risk.

A classic field inside information theories is the literature on business failure, where financial statement analysis plays an essential role. However, would information in the game be given in terms of financial data that participants have to analyze, it would introduce an asymmetry among participants where the more skilled ones would be expected to outperform. Rather than that, the goal of the experiment is to disentangle whether different risk profiles and overconfidence levels would produce predictable patterns when all participants are given the same, objective information. Consequently, we want information provided to participants to be given in the form of confidence intervals (average, high and low boundaries) of objective pieces of information such as expected GDP growth, Euribor rates, or clients' expected default rates.

Regarding the literature on banking efficiency, several measures of cost and profit efficiency are available (recall the discussion in Chapter 1). Berger and Mester (1997) provide a list of variables to be used to test cost and profit efficiencies (recall Table 1.3 in Chapter 1), which includes costs, prices, loan volumes and environmental variables such as nonperforming loans over total loans.

This provided, we proceed as follows in the experiment. First, information to be provided to participants about macroeconomic perspectives and client's expected solvency will be objective, presented in the form of confidence intervals, and updated period by period. Second, the cost structure of the banks will be an input, provided to participants as a given variable. Respondents may consequently implement their strategies in terms of loan prices and volumes granted. Finally, we control for the risky behavior of participants by measuring two ex post variables: their average ratio of NPL to total loans, as well as the ratio between prices granted to customers of high versus low qualities.

Consequently, the experiment that is described next in Section 8.3 was designed to make participants decide how much credit and at what price they would grant to a series of clients, given information available about their expected solvency and macroeconomic perspectives. The hypotheses to be tested seek to trace evidence of the effects that different risk profiles, in terms of prospect theory and overconfidence, might have over the policies participants implement. Consequently, we put special emphasis in several aspects of the game. First, we always provide subjects with objective information about economic perspectives and expected solvency, mostly in the form of confidence intervals. Second, we give them clear instructions of how variables in the game are interrelated and how to set their strategies. Finally, we implement a multi-period game where information is to be updated, as to reflect a business cycle that might either improve or worsen, in order to let participants' expectations play a relevant role —hence, perhaps, prospect theory and overconfidence effects might be traced.

8.3. BASICS OF THE GAME

In this section we explain the experiment in detail. This comes in three instances. First, subsection 8.3.1 deals with the basics of the game. Second, we explain how the experiment was conducted. This includes instructions provided to participants and recommendations they were given to help them setting their strategies. Finally, in subsection 8.3.3 we describe the *indicators* that describe how participants played, in accordance to our discussion in subsection 8.2.2. These indicators will be the dependent variables to be tested against the behavioral profile of each participant in Section 8.4. In what follows we explain the basics of the game.

8.3.1. The game

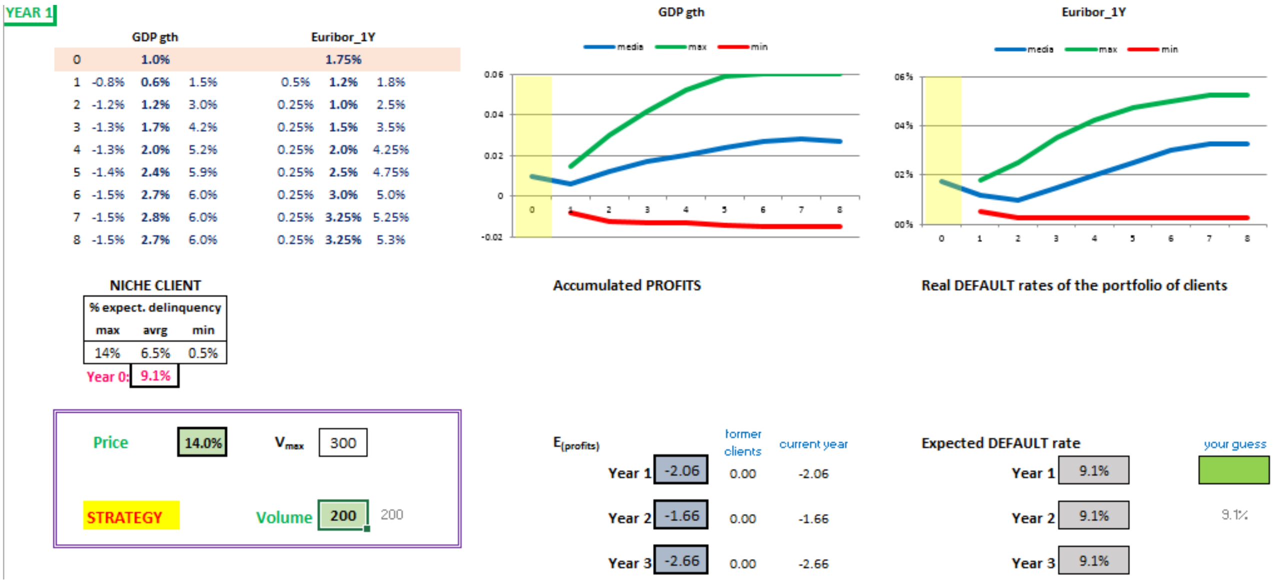
Each participant runs a bank that grants credit to customers. All participants play a similar game, facing identical situations and being given the same information set. However, they play individually with no reciprocal effects (a player's strategies don't affect other players' results). Nonetheless, they do play competitively: the objective of the game is to see which participant implements the best strategy in terms of profit maximization. The winner —the participant that earns the highest profit at the end of the game— of each session gets a prize of 60 euros. Five rounds with students were conducted for this experiment, about 20 to 30 pupils each one, for a total of 126 participants.

We devised a multi period game (6 periods) where at each stage the bank has access to a niche of clients (a different niche every period) asking for a 3-year loan. At each stage, participants have to decide how much credit and at what price they are willing to grant to that niche, given information available. Information provided to participants includes (a) the niches' expected default rates in the form of confidence intervals;[237] (b) macroeconomic perspectives (about GDP growth and Euribor_1Y rates), also presented in the form of confidence intervals; (c) calculations of (ex ante) expected profits and delinquency ratios given the participant's strategy, as well as (ex post) real profits and default rates after strategies have been set and information was updated.

Figure 8.1 shows a screenshot of the computer application for the game at period 1. Information provided includes macroeconomic perspectives (above), niche default rates and player strategies (to the left) and expected, as well as historical, profits and portfolio delinquency ratios (to the right). All these pieces of information are analyzed in what follows.

[237] Confidence intervals are given in three-point format: average values, high and low boundaries. Boundaries are explicitly said to be absolute limits that cannot be exceeded. That means, for instance, that if the expected default rate of a niche is (15%, 5%, 1%), the highest (lowest) default rate in all possible states of the world is 15% (1%). That also means, for instance, that if in period 1 we say the expected GDP growth for period 5 may range between (-1%, 1%, 3%), updated information in periods 2 to 4 cannot say that the expected GDP growth for period 5 may go higher than 3% or lower than -1%.

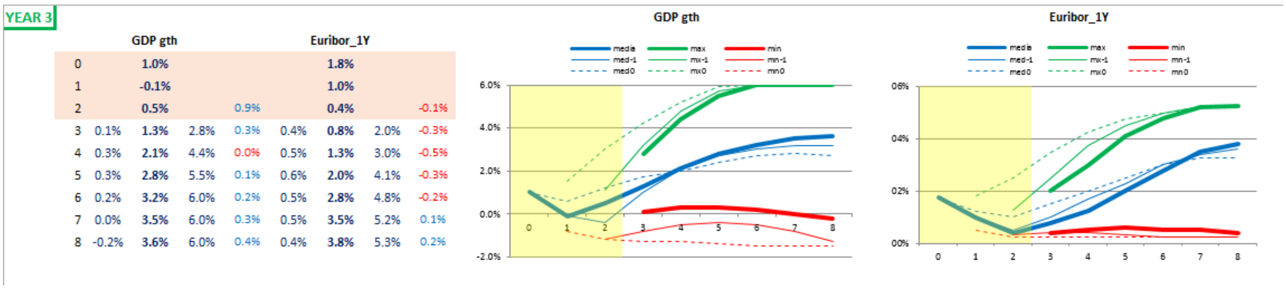
FIGURE 8.1 – Screenshot of the game at period 1



Source: Own elaboration

Macroeconomic data. At the beginning of each stage participants are given information about the economic perspectives, regarding expected GDP growth and Euribor_1Y rates, in terms of confidence intervals. Both numerical and graphical information are provided for periods 1 to 8 (it is a 6-period game, but at every period a 3-year loan is granted). Graphics allow for a more intuitive interpretation of the economic situation, particularly when information is updated in the following periods: confidence intervals use different colors, a thin line represents the last year estimation, a dotted line the initial one (period 1), and shadowed areas represent past periods, as we may see in Figure 8.2 for period 3.

FIGURE 8.2 – Updated macro information at period 3



Source: Own elaboration

Numerical data also provides information of changes in economic perspectives: positive and negative variations in average estimations for GDP growth and Euribor rates between two consecutive periods are highlighted in blue and red code, as we may see in Figure 8.2 above.

<u>Information not given to participants</u>. GDP growth rates were designed to range from -1.5% to 6.0% with an average of 2.5%. Boundaries widen the farther the estimation from the current period. On average, the amplitude of the intervals would be about 1% for a next year estimation, 1.75% two years ahead, 2.5% three years ahead, and so on —though actual ranges may vary to some extent. Euribor rates

were designed to vary, intuitively, in accordance with GDP perspectives, with lower (higher) rates being correlated with weak (stronger) GDP perspectives. Since participants would play a simulated game first for practice, and then the 'real game' where prizes were distributed, we devised 2 alternative economic scenarios. They are summarized in Figure 8.3 by the ex post economic data at the end of the game.

FIGURE 8.3 – Scenarios of the simulated and real games at period 8

Source: Own elaboration

As we may see, we designed a scenario for the real game where the macroeconomic perspectives tended to improve —as it would happen during the upswing of the economic cycle.

Niche default rates. Information about the expected default rates of the niche clients at each stage was given in terms of confidence intervals. Table 8.1 summarizes the intervals provided for all 6 niches.

TABLE 8.1 – Expected default rates of all niche clients

		% expected default rate		
		max	mean	min
A	C1	14%	6.5%	0.5%
B	C2	10%	5%	2%
B	C3	9%	4%	1%
A	C4	16%	7%	0%
A	C5	18%	7.5%	1%
B	C6	11%	5%	1%

Source: Own elaboration

Participants were only said that maximum, minimum and average default rates are related with the weakest, strongest and average GDP performance, but that the explicit mathematical relationship between GDP growth and delinquency was unknown. In addition, players were advised, when setting their price and credit volume strategies, to infer the expected default rate of that niche client given the information provided for that niche and for economic perspectives. As a starting clue, and only for period 1, explicit information about the true default rate of the niche client in the previous period (period 0, before the game started) is provided. For the subsequent periods that information is not provided, since players may learn the real (ex post) default rates of their portfolios once economic scenarios are updated.

Information not given to participants. The six niche clients in the real game are of two types, according to their expected default rates. Type A niches are riskier than Type B, both because they exhibit wider intervals and because downside risk is substantially higher. Real *ex post* default rates were estimated given GDP performance. In particular, reference GDP growth rates were estimated as 2/3 the current (ex post) rate + 1/3 the previous year rate. Then, real default rates were set to fall at the equivalent point in the interval as the reference GDP rate within the (-1.5%, 2.5%, 6.0%) interval above mentioned. For instance, for niche C1 when the real ex post GDP growth rate at period 1 happened to be -0.1% and the previous year rate was 1.0% we have:

$$Reference\ GDP\ rate = \frac{2}{3}(-0.1\%) + \frac{1}{3}(1.0\%) = 0.267\%. \tag{8.1}$$

Since 0.267% lies in the bottom half of the interval, (-1.5%, 2.5%), we set the real *ex post* default rate for period 1 to lie at the (linearly) equivalent point within the bottom range (14%, 6.5%) —see data in Table 8.1— which is equivalent to compute

$$Real\ default\ rate = 14\% + ratio(0.267\% - 2.5\%), \tag{8.2}$$

where ratio = (14% - 6.5%) / (2.5% - (-1.5%)) = -1.88 measures the effect an increase of one percent in the GDP rate reduces the default rate. That makes the real (ex post) default rate of client C1 in period 1 equal to 10.69% in our example.

Strategy: At every period, participants must analyze the information available and determine their strategy. Strategies are defined in terms of two variables: the **PRICE** at which they are willing to grant credit to that niche of clients, and the volume of credit granted, **VCC**, to that niche. For such purpose, they are helped with automatic calculations —right-hand side of the screenshot in Figure 8.1— of the expected profits they ought to maximize (see 'profit calculations' below). Participants were told to proceed as follows. First, have an initial guess of the expected default rate for that niche market (cell 'your guess' in Figure 8.1) and then set a PRICE. They were required to set a price that ranges within 10.0% and 20.0%. For such price, they are given the maximum volume demanded by the niche market, V_{max}, which follows a linear demand function[238] for credit of the type

$$V_{max} = 1{,}000 - 5{,}000 \cdot PRICE, \tag{8.3}$$

hence credit volumes may range from 0 to 500 euros. Finally, participants must decide whether they are willing to grant the maximum volume of credit demanded, that is, VCC = V_{max}, or they prefer to be more

[238] The demand function was not provided to subjects, but they were obviously given the outcome V_{max}.

conservative to set a V such that $0 \leq V < V_{max}$. This allows us to measure which participants are being more conservative in terms of volume, too —rather than having PRICE as the single decision variable. Thus, we observe two variables per participant, PRICE and VCC, that may not clear the market (whenever VCC < V_{max}). In instructions they were advised to do so depending on “how sure you are your strategies are going to be profitable”, since setting VCC = 0 makes fixed costs equal to zero as well (saving 3 euros per niche, see ‘profit calculations’ next for further information).[239]

Profit calculations. To help participants set their strategies, the computer application provides *ex ante* estimations of profits and portfolio default rates. Players were also given information, before the game starts, of the mathematical expression for the profit function (income minus costs) used to derive those values, though they were said this was only given for their better understanding of the game and were advised to follow the calculations instead. The (expected) revenue function was set as

$$Income = VCC \cdot PRICE \cdot (1 - m_e) - m_e \cdot VCC, \tag{8.4}$$

where m_e is the expected default rate of the niche (provided by the player or the estimation by default otherwise).[240] The cost function is

$$Costs = fixed + (Euribor + vc) \cdot VCC. \tag{8.5}$$

That is, the bank faces 3 types of costs: (a) a fixed cost (*fixed*) of 3 euros per period and number of niche clients active (i.e., those for which a volume VCC ≠ 0 was granted during the last 3 years); (b) a variable cost (*Euribor*) equal to the (expected) Euribor_1Y rate provided (representing the cost of the deposits needed to fund credit granted); and (c) another variable cost (*vc*) of 2.0%, interpreted as the cost of managing a higher volume of credit.

From (8.4) and (8.5) the expected profit function is

$$E_{PROFITS} = [(1 - m_e) \cdot PRICE - (m_e + Euribor_e + 2.0\%)] \cdot VCC - 3, \tag{8.6}$$

whereas the real (ex post) profits observed are simply

$$PROFITS = [(1 - m) \cdot PRICE - (m + Euribor + 2.0\%)] \cdot VCC - 3, \tag{8.7}$$

where m and *Euribor* replace the ex ante expectations m_e and $Euribor_e$.

Finally, on the right hand side of the screen, participants were also given information about the delinquency ratios of their portfolios. Regarding expected delinquency, subjects may make their own

[239] For indicators estimation (see section ‘indicators’), when a subject sets VCC = 0 we make PRICE = 20% —i.e., the price that should be offered to have zero demand— disregarding the actual value the participant has set. We do so in order to have indicators that are homogeneous across participants: judges set VCC = 0 after they tried different prices (sometimes even providing no data for PRICE), so the last price they set may be not representative. This correction does not apply to any other case since, as explained, we want to observe both price and volume strategies that might not clear the market.

[240] That income function makes two implicit assumptions. First, a default means the bank recuperates neither interests nor capital from that proportion m_e. Second, for simplicity we assume the total credit granted to a niche in all three years the credit is active is equal to the initial VCC granted. That may be interpreted as a line of credit to a niche of clients that is renewed annually with independence of the default rate incurred in previous year(s). Participants were informed of both assumptions.

estimations (cell 'your guess' in Figure 8.1). Otherwise, if that cell is blank, the computer sets an expected default rate by default: in period 1, the real default rate of the niche in period 0; in subsequent periods, the real default rate of his or her current portfolio of clients. The real (historic) default rates are also provided. They are computed simply as the weighted average (weighted by VCC) of the observed default rates of all active niche clients in the participant's portfolio.

Optimal (*ex post*) **strategies**. We may compare the participants' strategies with what would be the optimal *ex post* strategies (i.e., once we know in period 8 how the economy actually performed). We compute them as follows. Setting VCC = 1,000 – 5,000 · PRICE in equation (8.7) and deriving with respect to PRICE we have the optimal strategy

$$PRICE^* = \frac{1{,}000+(5{,}000-1{,}000)\cdot\bar{m}+5{,}000\cdot(\overline{Euribor}+2.0\%)}{2\cdot 5{,}000\cdot(1-\bar{m})}, \qquad (8.8)$$

where $\bar{m}$ and $\overline{Euribor}$ are the average values of the default and Euribor rates, respectively, during the three years the loan to that niche client was operative. Table 8.2 summarizes the optimal ex post strategies for all six niches in the game.

TABLE 8.2 – Optimal ex post strategies for all niche clients

		m1	m2	m3	m4	m5	m6	m7	m8	average	PRICE*	VCC*
A	C1	10.7%	10.6%	8.4%						9.9%	17.0%	149.6
B	C2		7.8%	6.3%	4.9%					6.3%	15.0%	248.3
B	C3			5.3%	3.9%	3.6%				4.2%	14.3%	282.6
A	C4				6.7%	6.1%	6.1%			6.3%	16.1%	197.1
A	C5					6.7%	6.6%	6.0%		6.4%	16.3%	186.2
B	C6						4.5%	4.0%	3.4%	4.0%	14.7%	264.3
										type A	16.4%	16.4%
										type B	14.7%	14.7%
										price ratio	**1.119**	**1.117**

Source: Own elaboration

These computations are helpful to confirm that type A clients should be granted a higher price, given their riskier profile, but taking the economic perspectives into account, too. The average optimal price for niches of type A is higher than for type B (16.4% vs. 14.7% in both average —blue— and volume-weighted average —green— data), as expected. The price ratio suggests an optimal price to type A clients that is a 12% higher (in relative terms, for a price ratio of about 1.12) than to type B. This information will be used as a benchmark for a 'quality indicator' later on (see section 'indicators').

8.3.2. Instructions to participants

Participants were instructed how to play the game in three steps. Firstly, they were given an extensive explanation of the game described above. Secondly, after being provided a set of written instructions that summarized all that information, participants had time to play a simulated version of the game, the whole six periods, for practice. Finally, after all participants confirmed they understood the game and felt ready, they completed the strategy game where a series of prizes for winners in terms of maximum profits were granted as an incentive to play.

In regards to the game structure, participants were also instructed how to play this multi-period game. The first screen they see shows how the game starts in 'year 1', where players must set their strategy for that niche given information available. Since in every period a 3-year loan is granted, participants are provided with an estimation of $E_{PROFITS}$ for the subsequent three periods (years 1, 2 and 3). After they set their strategies, they move on to a second screen where (i) macroeconomic information is updated, and (ii) *ex post* profits and delinquency ratios are computed and shown to participants. Now in 'year 2' a new niche client is available, so participants must decide a new strategy, PRICE and VCC, for granting a 3-year loan to the new niche, given the updated information available.[241] Then they move on to a third screen, where macroeconomic information is updated, ex post profits and delinquency ratios are computed… and so on until 'year 6', the last one for which participants have to set their strategies.

Finally, participants were given these instructions to help them setting their strategies: *"First, in order to set your strategy (PRICE, VCC) at each stage, always follow this sequence: (1) guess a delinquency rate of the niche based on the information available; (2) set a PRICE between 10.0% and 20.0%; V_{max} will be consequently updated and the computer will provide the $E_{PROFITS}$ for the expected default rate, PRICE and V_{max}; (3) set VCC; again, the $E_{PROFITS}$ will be updated; you must decide whether you grant credit to that niche or not and, if you do, whether you set VCC = V_{max} or a lower volume; (4) finally, repeat steps 1 to 3 as many times as you need it to set your definitive strategy (PRICE, VCC). Second, please note the computer application helps you to calculate $E_{PROFITS}$ given the inputs being set (m_e, PRICE, VCC). Be aware these are the $E_{PROFITS}$ that you set; this expectation may fulfill or not depending on whether (a) the economic scenario follows the path you anticipated; and (b) the strategy you consequently implemented is indeed optimal. Therefore, please be advised when setting your strategies that $E_{PROFITS}$ are just an aid. On one hand, not granting credit (VCC = 0) when you think a niche may not generate profits allows you to save a fixed cost of 3 euros. On the other hand, if you decide to grant credit, granting VCC = V_{max} or a lower volume should depend on how sure you are this niche client is going to render you profits rather than losses."*

8.3.3. Indicators – dependent variables

At the end of the game, each participant has provided 6x2 decision variables: that is, a pair (PRICE, VCC) they were willing to grant credit to each of the six niche clients. As described in subsection 8.2.2, based on this information we want to trace differences across participants regarding three types of indicators: their different strategies in terms of (i) prices and (ii) volumes, as well as controlling for their risky behavior by computing some (iii) quality indicators. These are explained in what follows:

[241] Now players have more information: the expected default rates of the new niche and macroeconomic perspectives as before, but the real default rate of clients in their portfolio and how the macroeconomic situation is evolving through time, too.

- **Price indicators**. We compute two estimators to trace differences in price strategies: $\mathbf{P_{avg}}$, the average price across the 6 niches; and $\mathbf{P_{vol}}$, the volume-averaged price across the niches. We compute the volume-averaged indicator as well because two subjects that set the same price to a give niche may not grant the same volume of credit as we allowed VCC < V_{max}.

- **Volume indicators**. We trace differences in volume strategies by computing two additional estimators, denoted for simplicity as 'VCC and VMAX indicators'. On one hand, $\mathbf{VCC_{ind}}$ sums all VCCs granted to the niches (i.e., $VCC_{ind} = \Sigma VCC$). On the other hand, $\mathbf{VMAX_{ind}}$ compares the volumes actually granted by the player with the demand faced for the PRICE she set. Thus, we compute $VMAX_{ind}$ as the ratio between VCC_{ind} and the sum of all V_{max} that would be demanded by each niche given the PRICEs the respondent had set.

- **Quality indicators**. We control for the risky behavior of participants by computing two types of indicators. First, the **NPL** indicator measures the average ratio of non-performing to total loans. Second, we compare the prices granted to customers of low (type A) versus high (type B) qualities. Likewise we did with price indicators, we obtain two indicators for this purpose: $\mathbf{Q_{avg}}$ is simply the ratio of the two averaged prices (average price to type A over average price to type B), while $\mathbf{Q_{vol}}$ sets a similar ratio but for volume-weighted average prices. Table 8.2 sets a benchmark to these quality indicators: the optimal ex post strategies entail the quality ratios 1.119 and 1.117 for mean and volume-average data, respectively. Hence, when indicators Q_{avg} and Q_{vol} of a given participant are well below those levels it may be attributed to an aggressive pricing strategy implemented to low-quality borrowers.

Table 8.3 summarizes all these seven indicators, which are meant to be the dependent variables in the hypothesis testing (Section 8.5).

TABLE 8.3 – Summary of game indicators

Variable	Values	Interpretation	Calculation	Literature
P_{avg}	P^* → min 10.0% - max 20.0%	↓ Price → ↑ risk strategy	average price across 6 niche clients	Defining relevant indicators of the game: Berger and Mester (1997)
P_{vol}			volume-weighted average price across 6 niches	
VCC_{ind}	VCC_{ind}^* → min 0 - max 500	↑ Volume → ↑ risk strategy	average volume of credit granted (6 niches)	
$VMAX_{ind}$	$VMAX_{ind} \leq 1$ where $VMAX_{ind} = 1$ → full credit at P^*		$VMAX_{ind} = VCC_{ind} / (\Sigma_{6\ niches} [V_{max} \mid P^*])$	
NPL	% of non-performing loans (min 0%)	↑ NPL → ↑ risk strategy	average *ex post* NPL ratio across 6 niche clients	Design and measurement of indicators: own elaboration
Q_{avg}	$Q_{avg} < 1$ → lower P to risky niches ($Opt._{expost}\ Q_{avg} = 1.119$)	↓ Quality → ↑ risk strategy	mean prices to costumers of high vs. low qualities	
Q_{vol}	Idem ($Opt._{expost}\ Q_{vol} = 1.117$)		idem, volume-weighted	

Source: Own elaboration

8.4. DATA

The same 126 participants that completed the behavioral tests in Chapter 7 competed in the experimental game. Table A.12 in the Appendix shows the raw data of direct responses provided by the subjects. Besides, Table A.13 in the Appendix shows the estimations that result for the game indicators (price, volume and quality indicators). Table 8.4 summarizes the basic univariate statistics of the game indicators that resulted. The respective histograms are also provided in Table A.14 in the Appendix.

TABLE 8.4 – Descriptive statistics of game indicators

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Average Price	126	5.67%	12.75%	18.42%	16.05%	0.0104	1.082	-.306	.216	.083	.428
Weighted Price	126	5.49%	12.19%	17.68%	15.40%	0.0109	1.190	-.457	.216	.029	.428
Volume	126	1459	371	1830	1103	269.10	72417.180	-.013	.216	.243	.428
Volume ratio	126	0.78	0.22	1.00	0.94	0.10	.011	-3.721	.216	19.528	.428
Non-performing loans	126	2.00%	5.11%	7.11%	5.95%	0.0033	.111	.144	.216	1.021	.428
Quality Ratio	126	0.70	0.69	1.39	1.02	0.11	.012	.491	.216	1.417	.428
Weighted Quality Ratio	126	0.69	0.74	1.42	1.02	0.10	.010	.390	.216	2.083	.428

Source: Own elaboration

Some variables provide a first intuition on how aggressive participants played on average. Thus, the volume ratio ($VMAX_{ind}$) is close to one, implying that they generally granted the maximum volume at a given price, and the quality ratios are both about 1.0, which means they did not differentiate low and high quality borrowers, especially if we compare this with the optimal ex post benchmark ratio 1.12. Average price, total volume and NPL satisfy the hypothesis of normality, as we may see in Table 8.5.[242]

TABLE 8.5 – Normality test for the game indicators

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Average Price	.066	126	,200*	.990	126	.515
Weighted Price	.089	126	.015	.982	126	.087
Volume	.040	126	,200*	.996	126	.963
Volume ratio	.286	126	.000	.595	126	.000
Non-performing loans	.069	126	,200*	.983	126	.110
Quality Ratio	.084	126	.029	.974	126	.015
Weighted Quality Ratio	.078	126	.056	.970	126	.006

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Source: Own elaboration

[242] For further interpretation, Table A.7 in the Appendix provides the histograms of all variables in the experiment.

The only variable that is strongly rejected to be normal in both tests ($p < 0.01$) is volume ratio (*$VMAX_{ind}$*), not surprisingly since this indicator is bounded to 1. At $p < 0.05$ weighted price and quality ratio would not satisfy normality either.[243]

Finally, for analysis and exclusion of extreme values we proceed as in Chapter 7. Table A.15 in the Appendix provides a normal Q-Q plot and a box-and-whiskers plot for all variables. We will exclude only extreme values, not outliers, and only when normality tests suggests they indicate experimental error rather than high kurtosis. These rules being considered, four observations have been removed from two variables for a second re-test. These are three extreme values for $VMAX_{ind}$ and one more for volume-weighted quality ratio (Q_{vol}).

8.5. HYPOTHESIS TESTING AND RESULTS

The purpose of the experimental research is to test whether more aggressive profiles in terms of behavioral biases are correlated with more risky credit strategies in the game. Consequently, we first describe what an aggressive profile and a risky strategy are in terms of the independent and dependent variables in our model. Then it will be easier to interpret the hypotheses to be tested.

We define an aggressive profile as having at least one of the following features: a risk seeking profile, low loss aversion, and high degree of overconfidence. The second and third features are easy to trace: loss aversion is measured by the β parameter in the value function (the lower β the riskier the behavioral profile of the subject), while overconfidence is higher the higher $\boldsymbol{E}$ and $\boldsymbol{P}$, and the lower $\boldsymbol{M}$.

A risk seeking profile, however, could manifest itself through more complex instances. Regarding the utility function, we have two cases: (i) a convex utility in the positive domain ($\alpha^+ > 1$), hence the higher α^+ the more risk seeking (ceteris paribus for similar probability weights); and (ii) a convex utility in the negative domain ($\alpha^- < 1$), hence the lower α^- the more risk seeking (again, ceteris paribus). However, when it deals with the probability weighting function, things get more complex. The lower γ^+ implies the higher risk seeking behavior for gains of low probability only, but a risk averse behavior for gains of moderate and high probability. Likewise, the lower γ^- implies the higher risk seeking behavior for losses of moderate/high probability, but a risk averse behavior for losses of low probability.

Hence, how should we disentangle a risk seeking behavior according to the weighting function? We know the outcome of participants' strategies strongly depend on the clients' expected delinquency ratio that is provided in terms of a confidence interval. Besides, we set the highest probability of default of all 6 niches in the game to be below 20%. Consequently, a key assumption henceforth is that the

[243] However, for 126 observations the Central Limit Theorem ensures the validity of subsequent results.

probabilities we will consider relevant in terms of probability weighting are **moderate and high for gains and low probabilities for losses**. Hence, we define a risk seeking behavior also as (iii) the higher γ^{+} (for gains of high probability) and (iv) the higher γ^{-} (for losses of low probability).

Finally, we define a risky strategy as the one that sets lower prices (**P_{avg}** and **P_{vol}**), higher volumes of credit (**VCC_{ind}** and **$VMAX_{ind}$**), higher **NPL** ratios and lower quality ratios (**Q_{avg}** and **Q_{vol}**) —since these ratios are defined in terms of low to high quality clients.

8.5.1. Hypotheses

Given the description above of more aggressive profiles and riskier strategies, it is now easier to interpret the hypotheses to be tested in terms of three features: a risk seeking behavior, loss aversion and overconfidence.

Risk seeking. As described in Chapter 4, risk-seeking choices are observed in two types of decision problems (Tversky and Kahneman, 1992): the *favorite-longshot bias* and the *aversion to a sure loss*. Risk seeking has been claimed to explain several anomalies. For instance, the house money effect (Thaler and Johnson, 1990) and the status quo bias (Tversky and Kahneman, 1991). Framing has been claimed to make use of either loss aversion or diminishing sensitivity (Tversky and Kahneman, 1986). Probability weighting may lead to irrational advice, which helps explaining the favorite-longshot bias and the IPOs underpricing puzzle (Hens and Bachmann, 2008). Several authors have also related aversion-to-a-sure-loss to corporate management, including Shefrin (2008) and Shefrin and Cervellati (2011). Finally, Barberis and Huang (2008) explained that portfolio underdiversification would be a result from investors' overweighting the probabilities of extreme outcomes. Consequently, we want to test whether a risk seeking behavior could have a predictable effect over credit policies. We test the following set of hypotheses.

Hypothesis 1

H0: The more risk seeking, the lower the price charged to clients

1a – H0: The higher α^{+} the lower P_{avg}

1a – H0: The higher α^{+} the lower P_{vol}*

1b – H0: The lower α^{-} the lower P_{avg}

1b – H0: The lower α^{-} the lower P_{vol}*

1c – H0: The higher γ^{+} the lower P_{avg}

1c – H0: The higher γ^{+} the lower P_{vol}*

1d – H0: The higher γ^{-} the lower P_{avg}

1d – H0: The higher γ^{-} the lower P_{vol}*

1e – H0: The higher the risk seeking behavior (aggregate factor) the lower P_{avg}

1e – H0: The higher the risk seeking behavior (aggregate factor) the lower P_{vol}*

Hypothesis 2

H0: The more risk seeking, the higher the volume granted to clients

2a – H0: The higher α^+ the higher VCC_{ind}

2a – H0: The higher α^+ the higher $VMAX_{ind}$*

2b – H0: The lower α^- the higher VCC_{ind}

2b – H0: The lower α^- the higher $VMAX_{ind}$*

2c – H0: The higher γ^+ the higher VCC_{ind}

2c – H0: The higher γ^+ the higher $VMAX_{ind}$*

2d – H0: The higher γ^- the higher VCC_{ind}

2d – H0: The higher γ^- the higher $VMAX_{ind}$*

2e – H0: The higher the risk seeking behavior (aggregate factor) the higher VCC_{ind}

2e – H0: The higher the risk seeking behavior (aggregate factor) the higher $VMAX_{ind}$*

Hypothesis 3

H0: The more risk seeking, the higher the NPL ratio

3a – H0: The higher α^+ the higher NPL

3b – H0: The lower α^- the higher NPL

3c – H0: The higher γ^+ the higher NPL

3d – H0: The higher γ^- the higher NPL

3e – H0: The higher the risk seeking behavior (aggregate factor) the higher NPL

Hypothesis 4

H0: The more risk seeking, the lower the quality ratios

4a – H0: The higher α^+ the lower Q_{avg}

4a – H0: The higher α^+ the lower Q_{vol}*

4b – H0: The lower α^- the lower Q_{avg}

4b – H0: The lower α^- the lower Q_{vol}*

4c – H0: The higher γ^+ the lower Q_{avg}

4c – H0: The higher γ^+ the lower Q_{vol}*

4d – H0: The higher γ^- the lower Q_{avg}

4d – H0: The higher γ^- the lower Q_{vol}*

4e – H0: The higher the risk seeking behavior (aggregate factor) the lower Q_{avg}

4e – H0: The higher the risk seeking behavior (aggregate factor) the lower Q_{vol}*

Loss aversion. The second group of hypotheses refers to the effect of loss aversion over the game indicators. As described in Chapter 4, loss aversion has been claimed to explain anomalies in decision-making, like the endowment effect (Thaler, 1980), the disposition effect (Shefrin and Statman, 1985), the status quo bias (Samuelson and Zeckhauser, 1988), the equity premium puzzle (Benartzi and Thaler, 1995), how the number of market transactions would be reduced (Knetsch, 1989) or why consumers and managers would take fewer risks (Rabin, 2000). We could summarize the effects of loss aversion to be tested following Kahneman (2011): *"in mixed gambles, where both a gain and a loss are possible, loss aversion causes extremely risk averse choices"* (p.285). Consequently, we want to infer whether those risk averse choices have a predictable effect over credit policies by testing the following set of hypotheses:

Hypothesis 5

H0: The lower the loss aversion the lower the price charged to clients

5a – H0: The lower β_{avg} the lower P_{avg}

5a – H0: The lower β_{avg} the lower P_{vol}*

5b – H0: The lower β_{med} the lower P_{avg}

5b – H0: The lower β_{med} the lower P_{vol}*

Hypothesis 6

H0: The lower the loss aversion the higher the volume granted to clients

6a – H0: The lower β_{avg} the higher VCC_{ind}

6a – H0: The lower β_{avg} the higher $VMAX_{ind}$*

6b – H0: The lower β_{med} the higher VCC_{ind}

6b – H0: The lower β_{med} the higher $VMAX_{ind}$*

Hypothesis 7

H0: The lower the loss aversion the higher the NPL ratio

7a – H0: The lower β_{avg} the higher NPL

7b – H0: The lower β_{med} the higher NPL

Hypothesis 8

H0: The lower the loss aversion the lower the quality ratios

8a – H0: The lower β_{avg} the lower Q_{avg}

8a – H0: The lower β_{avg} the lower Q_{vol}*

8b – H0: The lower β_{med} the lower Q_{avg}

8b – H0: The lower β_{med} the lower Q_{vol}*

Overconfidence. This bias has been claimed to explain anomalies like excess volatility, under and overreaction (Daniel, Hirshleifer and Subrahmanyam, 1998), excessive trading (Odean, 1998, 1999), asset bubbles (Scheinkman and Xiong, 2003), the forward premium puzzle (Burnside et al., 2011), and sensation seeking (Grinblatt and Keloharju, 2009). Research on corporate finance suggests executives appear to be prone to display overconfidence (Moore, 1977), and helps explain the high rates of business failure (Camerer and Lovallo, 1999), high rates of M&A (Roll, 1986; Malmendier and Tate, 2005a,b), a lower dividend payout (Deshmukh et al., 2010) and higher cash holdings (Huang, Lambertides and Steeley, 2012). Finally, overconfidence has been related to the confirmation bias (Koriat, Lichtenstein and Fischhoff, 1980), the hindsight bias (Fischhoff, 1982b), the illusion of control (Barber and Odean, 2002), the self-attribution bias (Statman, Thorley and Vorkink, 2006) and portfolio underdiversification (Goetzmann and Kumar, 2008). Since we are using three different measures of overconfidence (Moore and Healy, 2008), we will test whether each measure or a combination of them are able to explain a riskier behavior by participants in the experiment. We state the following set of hypotheses:

Hypothesis 9

H0: The higher the overconfidence, the lower the price charged to clients

9a – H0: The higher overestimation (higher E) the lower P_{avg}

9a – H0: The higher overestimation (higher E) the lower P_{vol}*

9b – H0: The higher overplacement (higher P) the lower P_{avg}

9b – H0: The higher overplacement (higher P) the lower P_{vol}*

9c – H0: The higher overprecision (lower M) the lower P_{avg}

9c – H0: The higher overprecision (lower M) the lower P_{vol}*

9d – H0: The higher the overconfidence (aggregate factor) the lower P_{avg}

9d – H0: The higher the overconfidence (aggregate factor) the lower P_{vol}*

Hypothesis 10

H0: The higher the overconfidence, the higher the volume granted to clients

10a – H0: The higher the overestimation (the higher E) the higher VCC_{ind}

10a – H0: The higher the overestimation (the higher E) the higher $VMAX_{ind}$*

10b – H0: The higher the overplacement (the higher P) the higher VCC_{ind}

10b – H0: The higher the overplacement (the higher P) the higher $VMAX_{ind}$*

10c – H0: The higher the overprecision (the lower M) the higher VCC_{ind}

10c – H0: The higher the overprecision (the lower M) the higher $VMAX_{ind}$*

10d – H0: The higher the overconfidence (aggregate factor) the higher VCC_{ind}

10d – H0: The higher the overconfidence (aggregate factor) the higher $VMAX_{ind}$*

Hypothesis 11

H0: The higher overconfidence, the higher the NPL ratio

11a – H0: The higher the overestimation (the higher E) the higher NPL

11b – H0: The higher the overplacement (the higher P) the higher NPL

11c – H0: The higher the overprecision (the lower M) the higher NPL

11d – H0: The higher the overconfidence (aggregate factor) the higher NPL

Hypothesis 12

H0: The higher overconfidence, the lower the quality ratios

12a – H0: The higher the overestimation (the higher E) the lower Q_{avg}

12a – H0: The higher the overestimation (the higher E) the lower Q_{vol}*

12b – H0: The higher the overplacement (the higher P) the lower Q_{avg}

12b – H0: The higher the overplacement (the higher P) the lower Q_{vol}*

12c – H0: The higher the overprecision (the lower M) the lower Q_{avg}

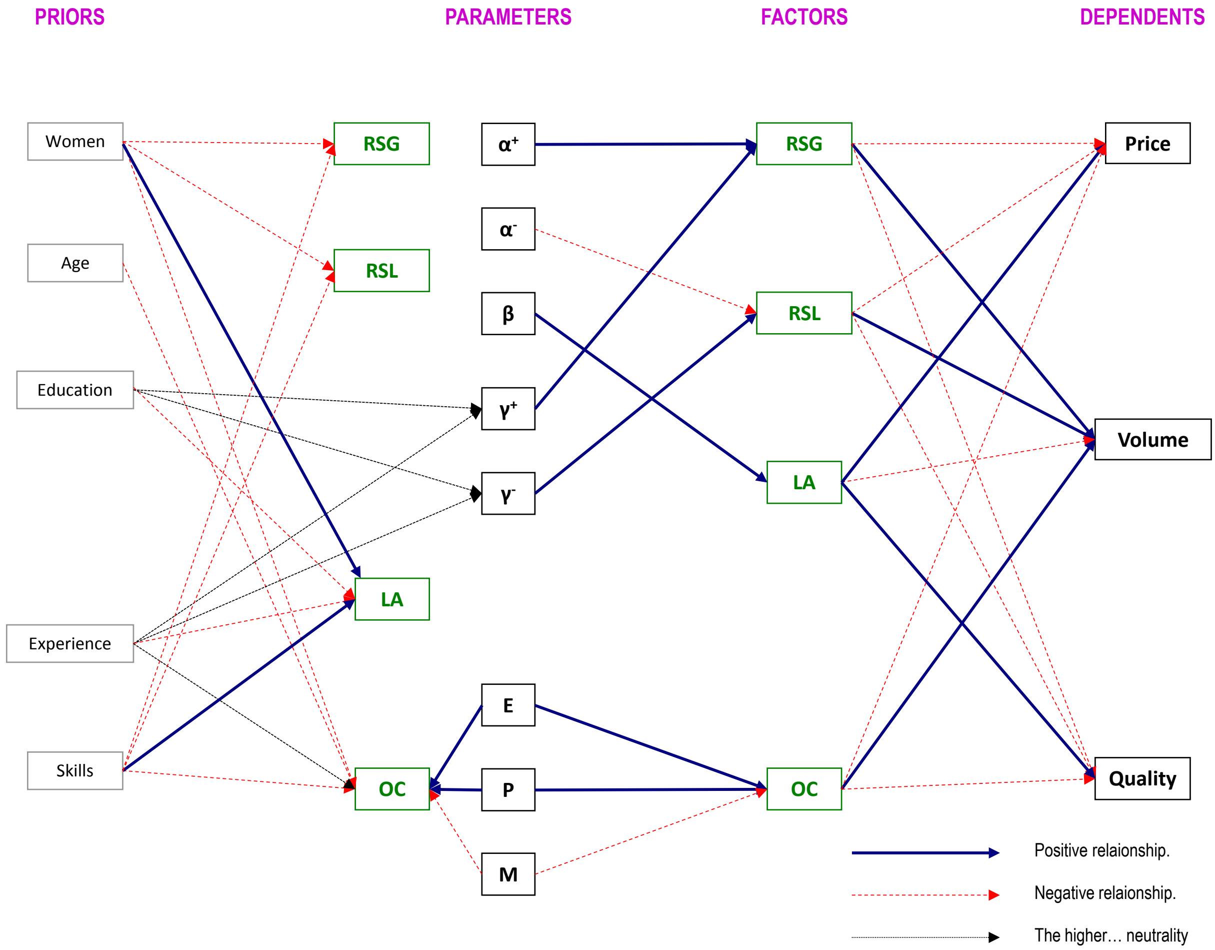
12c – H0: The higher the overprecision (the lower M) the lower Q_{vol}*

12d – H0: The higher the overconfidence (aggregate factor) the lower Q_{avg}

12d – H0: The higher the overconfidence (aggregate factor) the lower Q_{vol}*

The whole set of hypotheses may be summarized in Figure 8.4, which includes not only the twelve hypotheses in this chapter, but the relationship among priors and behavioral variables that were tested in Chapter 7. Note RSG, RSL, LA and OC in Figure 8.4 below stand for risk-seeking for gains, risk-seeking for losses, loss aversion and overconfidence, respectively.

FIGURE 8.4 – Summary of the hypotheses tested



Source: Own elaboration

8.5.2. Results

We conduct three types of analyses: variable analysis, factorial analysis and clusters. We analyze these results separately.

Variable analysis

The first way we test the hypotheses above is through a correlation analysis among behavioral variables and game indicators. Table 8.6 below summarizes the results.

TABLE 8.6 – Correlation matrix. Variables and indicators

Correlations

		Pavg	Pvol	VCCind	VMAXind (r)	NPL	Qavg	Qvol (r)
E	Pearson Correlation	-.040	-.055	.075	-.109	.075	.002	-.021
	Sig. (2-tailed)	.656	.542	.405	.232	.406	.982	.816
	N	126	126	126	122	126	126	125
P	Pearson Correlation	-.131	-.162	.127	-.069	.002	.096	.071
	Sig. (2-tailed)	.143	.071	.156	.451	.980	.285	.429
	N	126	126	126	122	126	126	125
Mmed	Pearson Correlation	.105	.057	-.030	.126	-.040	.117	,198*
	Sig. (2-tailed)	.244	.527	.741	.170	.656	.193	.028
	N	125	125	125	121	125	125	124
Mavg	Pearson Correlation	,184*	.127	-.110	.120	-.007	.055	.043
	Sig. (2-tailed)	.040	.159	.224	.191	.935	.545	.634
	N	125	125	125	121	125	125	124
alpha +	Pearson Correlation	-.113	-.030	.021	-.082	.087	-,242**	-.169
	Sig. (2-tailed)	.210	.738	.816	.368	.334	.006	.060
	N	126	126	126	122	126	126	125
alpha -	Pearson Correlation	.120	.160	-.076	.079	-.001	.073	.004
	Sig. (2-tailed)	.182	.073	.398	.385	.988	.416	.962
	N	126	126	126	122	126	126	125
gamma +	Pearson Correlation	-.122	-.088	.110	.169	,192*	-,258**	-,216*
	Sig. (2-tailed)	.173	.325	.221	.062	.031	.004	.015
	N	126	126	126	122	126	126	125
gamma -	Pearson Correlation	.061	.077	.119	,297**	,219*	.052	-.060
	Sig. (2-tailed)	.500	.394	.186	.001	.014	.566	.509
	N	126	126	126	122	126	126	125
βmed	Pearson Correlation	-.042	-.060	.022	-.055	-.065	-.071	-.085
	Sig. (2-tailed)	.640	.502	.804	.547	.470	.427	.349
	N	126	126	126	122	126	126	125
βavg (r)	Pearson Correlation	.021	.003	-.031	-.020	-.056	-.012	.005
	Sig. (2-tailed)	.817	.974	.734	.825	.537	.898	.955
	N	123	123	123	119	123	123	122

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own elaboration

In terms of price and volume, which are the decision variables to participants in the game, a few significant correlations are observed, all of them providing evidence that more aggressive profiles are correlated with more risky credit strategies. In particular, we observe: (i) γ^- is positively correlated with $VMAX_{ind}$ ($p < 0.01$), suggesting that more risk seeking participants tend to be more aggressive in terms of volume ratios granted (Hypothesis 2d* is satisfied); and (ii) M_{avg} is positively correlated with P_{avg} ($p < 0.05$), suggesting overconfidence —in terms of excessive precision to estimate future uncertainty— induces a more aggressive price policy (it reduces price, satisfying Hypothesis 9c). At $p < 0.1$ we also observe: (iii) P is negatively correlated to P_{vol} (the more overplacement the more aggressive price strategy, satisfying Hypothesis 9b*); (iv) α^- is positively correlated to P_{vol} (again more aggressive price policies are associated to more risk seeking profile to avoid sure losses, satisfying Hypothesis 1b*); and (v) γ^+ is also positively correlated with $VMAX_{ind}$ (hence satisfying Hypothesis 2c*).

Notwithstanding, it is in terms of quality where we obtain the more relevant results. First, the risk profile for gains has the most powerful ability to predict quality performance. On one hand, γ^+ is correlated (vi) positively with NPL ($p < 0.05$); and (vii) negatively with Q_{avg} ($p < 0.01$) and (viii) with Q_{vol} ($p < 0.05$), satisfying Hypotheses 3c, 4c and 4c*. On the other hand, α^+ is also negatively correlated (ix) to Q_{avg} ($p < 0.01$) and (x) to Q_{vol} ($p < 0.10$), satisfying Hypotheses 4a and 4a*. Second, additional evidence of a behavioral profile that is correlated with quality performance is obtained in terms of (xi) M_{med} is positively correlated with Q_{vol} ($p < 0.05$), suggesting overprecision reduces quality performance, and (xii) γ^- is positively correlated with NPL ($p < 0.05$).

To sum up, we find twelve pieces of evidence that an aggressive behavioral profile (more risk seeking, higher overconfidence) is significantly correlated to riskier credit strategies, particularly in terms of providing credit to low-quality customers at a lower price. On the contrary, we did not find a single piece of evidence in the opposite direction. Only mention we could not trace evidence of loss aversion, a classic in the behavioral literature, being able to explain credit policies in any sense.

Finally, we conduct a regression analysis with a stepwise procedure for variable selection. Results are summarized in Table 8.7 —more complete information is available in Table A.16 in the Appendix. We see the results support the main findings of the correlation analysis above. First, higher overprecision (lower M_{avg} or M_{med}) causes a more aggressive pricing policy (reduces P_{avg}) and reduces quality (Q_{vol}). Second, higher γ^- (which implies a risk seeking behavior for losses of low probability) causes a more aggressive volume policy (in terms of $VMAX_{ind}$) and increases default ratios (NPL). Third, higher γ^+ (which implies a risk seeking behavior for gains of medium and high probabilities) reduces the quality performance (both indicators Q_{avg} and Q_{vol}) of the credit policy implemented.

We find these results strongly consistent with what the game design was intended for: with all relevant information provided in terms of confidence intervals (macroeconomic information, expected default rates) and probabilities of default, both correlation and regression analysis evidence that an excessive precision to estimate future uncertainty and distortion of probabilities do bias credit policies by decision makers. Moreover, they do so in the expected direction: higher overprecision and a risk seeking profile cause more aggressive price–volume policy and reduce quality performance. Obviously, the explanatory power of these models is very low since we are leaving aside alleged key factors such as expected GDP growth and default rates, but the fact that R^2 is significantly different from zero in any case highlights the effect that behavioral biases have on credit policies implemented.

TABLE 8.7 – Regression models. Game indicators to behavioral biases

	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable	P_{avg}	$VMAX_{ind}$	NPL	Q_{avg}	Q_{vol}
Constant	15.743	0.920	5.812	1.091	1.047
E	-	-	-	-	-
(signific.)					
P	-	-	-	-	-
(signific.)					
M_{med}	-	-	-	-	0.075
(signific.)					0.021
M_{avg}	0.655	-	-	-	-
(signific.)	0.043				
α^+	-	-	-	-	-
(signific.)					
α^-	-	-	-	-	-
(signific.)					
γ^+	-	-	-	-0.108	-0.082
(signific.)				0.004	0.012
γ^-	-	0.068	0.263	-	-
(signific.)		0.001	0.015		
β_{med}	-	-	-	-	-
(signific.)					
β_{avg}	-	-	-	-	-
(signific.)					
R^2	0.034	0.088	0.048	0.066	0.089
adj. R^2	0.026	0.080	0.040	0.059	0.073

Source: Own elaboration

Factorial analysis

We conduct a factor analysis of all seven game indicators. In a first stage we obtain the results in Table 8.8. The Principal Component Analysis (PCA) posits two factors. The second one is easy to be given an intuitive meaning: all indicators that determine the quality profile of the credit policy are synthetized into a factor we denote **QUALITY**. The intuition is correct about how the indicators load on it: NPL is negatively related to QUALITY while Q_{avg} and Q_{vol} are positively related. The first factor, instead, requires further interpretation. Here, price and volume indicators are clustered together. Price and volume are the variables that determine a participant's strategy, and by the way they load on this factor —price indicators positively and VCC moving in the opposite direction— we may interpret that the higher the factor value, the more conservative (higher price, lower volume) the participant's strategy. However, the fact that $VMAX_{ind}$ loads positively goes against this interpretation.[244]

[244] Participants with lower $VMAX_{ind}$ ratios granted less credit than the maximum volume demanded by the market at that price. Consequently, lower $VMAX_{ind}$ ratios evidence a more conservative policy in terms of volume. However, for a factor defined as the higher the more conservative, this would require a negative load in Table 8.8, rather than positive.

TABLE 8.8 – Factorial analysis. Game indicators – First stage

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.489
Bartlett's Test of Sphericity	Approx. Chi-Sq	962.204
	df	21
	Sig.	.000

Rotated Component Matrix[a]

	Component	
	1	2
P_{avg}	.980	.086
P_{vol}	.945	-.020
VCC	-.909	-.100
$VMAX_{ind}$ (r)	.410	-.045
NPL	.088	-.704
Q_{avg}	.061	.886
Q_{vol} (r)	.094	.901

Extraction Method: Principal Component Analysis

Rotation. Varimax Normalization with Kaiser.[a]

a. Rotation converged in 3 iterations.

Source: Own elaboration

Consequently, we move forward to a second stage by excluding $VMAX_{ind}$ from the factorial analysis. We obtain the results summarized in Table 8.9.

TABLE 8.9 – Factorial analysis. Game indicators – Second stage

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.660
Bartlett's Test of Sphericity	Approx. Chi-Sq	511.610
	df	15
	Sig.	.000

Rotated Component Matrix[a]

	Component	
	1	2
P_{avg}	.964	.056
P_{vol}	.936	.009
VCC	-.904	-.065
NPL	.078	-.739
Q_{avg}	.071	.900
Q_{vol} (r)	.158	.907

Extraction Method: Principal Component Analysis

Rotation. Varimax Normalization with Kaiser.[a]

a. Rotation converged in 3 iterations.

Source: Own elaboration

Now the KMO measure improves significantly, with the first factor integrating prices and volumes in a coherent way. We denote this factor **STRATEGY** (since it is prices and volume what determines a participant's strategy), which is interpreted as the higher the factor, the more conservative strategy.

These factors being considered, we may again conduct both a correlation and regression analysis against behavioral factors and variables in Chapter 7 to test the hypotheses above. The correlation analysis is summarized in Table 8.10. Additional information is provided in Table A.17 in the Appendix. The regression analysis yields similar results, provided in Tables 8.11 and Table A.18 in the Appendix.

TABLE 8.10 – Correlations among factors

Correlations

		OC	Gains	Losses	Loss_av
Strategy	Pearson Correlation	-.097	-.096	.071	.018
	Sig. (2-tailed)	.284	.288	.428	.845
	N	124	125	125	125
Quality	Pearson Correlation	-.012	-,266**	-.069	-.040
	Sig. (2-tailed)	.897	.003	.445	.657
	N	124	125	125	125

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own elaboration

TABLE 8.11 – Regression models. Game factors to behavioral factors and variables

Model	1	2
Dependent variable	**Strategy**	**Quality**
Constant	-	-0.016
OC	-	-
(signific.)		
Gains	-	-0.261
(signific.)		0.003
Losses	-	-
(signific.)		
Loss Aversion	-	-
(signific.)		
R^2	-	0.071
adj. R^2	-	0.063

Model	1	2
Dependent variable	**Strategy**	**Quality**
Constant	-	0.645
E	-	-
(signific.)		
P	-	-
(signific.)		
M_{med}	-	-
(signific.)		
M_{avg}	-	-
(signific.)		
α^+	-	-
(signific.)		
α^-	-	-
(signific.)		
γ^+	-	-1.029
(signific.)		0.003
γ^-	-	-
(signific.)		
β_{med}	-	-
(signific.)		
β_{avg}	-	-
(signific.)		
R^2	-	0.072
adj. R^2	-	0.064

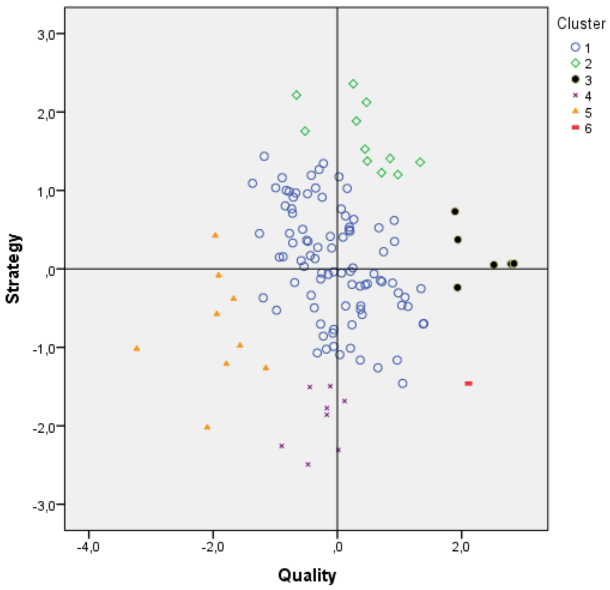
Source: Own elaboration

On one hand, in regards to the correlations in Table 8.10, when we analyze the correlations among factors we again obtain clear evidence that the risk profile for gains affects the quality performance of the credit policy implemented. In particular, this traces evidence that the more risk seeking for gains the lower the quality performance (i.e., the more risky price strategy to low-quality customers), coherent with our predictions.[245] On the other, regarding the regression models in Table 8.11, we may see in the table on the left-hand side —which provides the regressions among factors— that the more risk seeking for gains causes a lower quality performance (i.e., a riskier price strategy to low-quality). In particular, the table on the right-hand side —which provides the same information on game factors to behavioral variables— shows this causality is due to γ^+ in particular.[246]

Cluster analysis

We end the statistical analysis of the experimental results with a cluster analysis. Different clustering alternatives were analyzed, considering different methods and analyses for both variables and factors. The results that revealed easier to interpret were a clustering in terms of game factors,[247] Strategy and Quality, where six different clusters were obtained. Results are summarized in Figure 8.5.

FIGURE 8.5 – Cluster analysis



Source: Own elaboration

[245] We also extend this analysis (see Table A.13 in the Appendix) for two types of correlations: one between behavioral variables and credit factors, the other between behavioral factors and credit indicators. On one hand, we find evidence that it is both α^+ and γ^+ which feed this behavior, since they are significantly and negatively correlated to Quality. This way, participants that were less risk averse (due to either a utility curvature that is closer to linearity or a lower distortion of probabilities) were willing to grant credit to low-quality borrowers at a lower price. On the other hand, there is also evidence that the risk profile for GAINS is significantly correlated ($p < 0.01$) with the three individual measures of quality (for NPL, $p < 0.10$). Hence, Hypotheses 3e, 4e and 4e* would be satisfied for the aggregate factor GAINS.

[246] Table A.14 in the Appendix also provides the regressions of game indicators to behavioral factors. There we may see an apparent contradiction: there is a causality effect of LOSSES on $VMAX_{ind}$ and NPL that is positive, whereas in Chapter 7 we defined higher LOSSES imply more risk aversion; hence, the regression results would say "the more risk aversion, the higher $VMAX_{ind}$ and non-performing loans", contrary to our Hypotheses. However, we saw in Chapter 7 as well that it is only true that higher γ- implies more risk aversion for medium/high probabilities. For low probabilities instead, which are the relevant ones in our game, the interpretation would be the opposite. Then, the results are coherent with the Hypotheses and results on correlations (Table 8.6) and regressions (Table 8.7) at the variable level.

[247] We will work with 125 observations because one outlier was excluded from variable Q_{vol}, which loads on Quality factor. Additionally, one more observation is lost for OC factor, since we had a missing value for M values from the beginning.

We may observe the largest cluster is centered both in terms of Strategy and Quality, while the minor groups represent sparser credit policies. Table 8.12 summarizes the descriptive statistics (mean value and standard error of the mean) for each cluster in terms of the six behavioral and game factors.

TABLE 8.12 – Cluster analysis. Descriptive statistics

		OC		GAINS		LOSSES		LOSSAVERS		STRATEGY		QUALITY	
Cluster	**N**	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
1	90*	.008	.108	-.114	.099	.024	.105	-.079	.105	.073	.074	-.035	.069
2	11	-.302	.196	-.218	.323	-.155	.282	.398	.330	1.676	.125	.422	.178
3	6	-.215	.411	.104	.396	.101	.468	-.415	.210	.175	.136	2.320	.184
4	8	-.008	.491	.945	.491	-.453	.415	.172	.313	-1.922	.135	-.267	.115
5	9	.324	.277	.515	.269	.252	.337	.400	.402	-.790	.241	-1.925	.188
6	1	-.184		-.342		-.224		-.657		-1.461		2.110	

* Data for OC includes 89 observations

Source: Own elaboration

FIGURE 8.6 – Cluster analysis. Dispersion diagrams for mean values

Source: Own elaboration

In addition, Figure 8.6 provides a series of dispersion diagrams that use these mean values to have an intuition on how the different behavioral profiles of each cluster might affect the credit strategies they set. However, we emphasize this interpretation should be carefully considered as any statistical analysis based on correlations or causality effects are unsound at this level.[248]

A first apparent result based on this interpretation is that the largest cluster (cluster 1) would not only include participants that exhibited a neutral strategy and quality factors, but that these participants were generally neutral as well in terms of any of the four behavioral factors that summarize overconfidence and risk profile. Consequently, it is the behavior of the smaller groups what needs to be explained: what happens when a group of participants is biased? Will their strategies and quality vary in a predictable manner? To answer that question we conduct an ANOVA test for differences of means across clusters, to find significant evidence ($p < 0.05$) that the clusters are different in terms of risk seeking for gains, GAINS.

8.6. CONCLUSIONS

We designed an original business simulation game that replicates the basics of the decision-making process of a bank granting credit to customers under conditions of uncertainty and risk. In order to test whether overconfidence and prospect theory are able to explain the excessive lending by retail banks, we organized a series of sessions where 126 under and postgraduate students participated in an experiment that was divided in two parts. The first part consisted of some short tests to measure the participants' level of overconfidence and risk profile according to prospect theory, with the results described in Chapter 7. The second part was the experimental implementation of the simulation game itself, which was described in this Chapter 8. Several hypotheses about the effects of risk seeking, loss aversion and overconfidence were tested. In what follows we summarize the main results obtained.

First, we found large evidence that aggressive behavioral profiles —high levels of overconfidence and risk seeking— are correlated to riskier credit strategies, particularly in terms of providing credit to low-quality customers at a lower rate. We do not find a single piece of evidence in the contrary direction, neither we are able to trace evidence that loss aversion has any effects on credit policies implemented.

Second, the results are consistent with what the game design was intended for: participants were given information in terms of confidence intervals and probabilities of default, and the results obtained suggest that higher overprecision and the risk profile for gains (mostly attributable to distortion of probabilities) foster lower prices, higher volumes of credit, and reduce quality. The most consistent result is that of distortion of probabilities fostering lower loan prices to low-quality customers.

[248] Having only six observations (clusters) invalidates the statistical significance of any correlations or regression analyses. Moreover, much information is lost when we use average values as representative of all individual observations in a cluster.

Third, the effects of behavioral biases over credit quality are also the most significant in terms of the external validity of the results. Participants in the experiment were aware their strategies were to be measured and scrutinized in terms of credit prices and volumes. Hence, their strategies might particularly be affected by a strategic behavior: when a given participant was behind in the game (losing in terms of profits), she might make weird decisions because she had nothing to lose. However, participants were not aware that their behavior in terms of quality was also scrutinized (Levitt and List, 2007). This is good news, since the most significant results of the experiment are the effects of overprecision and probability distortion over quality performance.

This research represents a first effort to explore the potential effects of behavioral biases over credit policies. Time constraints to implement both a series of psychological tests and the simulation game imposed the requirement in this experiment that only one repetition of the game was to be performed.[249] Therefore, the external validity of the results might be improved in future research if several rounds of the game with randomized economic scenarios are implemented. This would help mitigate the effects of a strategic behavior and avoid any randomization bias (Viera and Bangdiwala, 2007), also introducing the possibility to test the debiasing effects of learning and experience.

Finally, some other limitations of the experiment could be considered for future replications —they follow in order. Firstly, it would be interesting to extend the way we tested the behavioral biases of the participants to other tests and elicitation methods available, such as cumulative prospect theory, non-parametric methods, and others. Secondly, a strong result we obtain in the experiment is in terms of the effects of overprecision, but in Chapter 7 we found that the overprecision measures were unstable at the individual level for different refinement methods —thus, the validity of the results depend on future re-tests with enhanced methods. Finally, the incentives in the game and the absence of penalties for excessive risk taking might have biased the results. This is a common drawback in any kind of experimental research, and future versions of this game should try to solve it. Notwithstanding, we may argue two reasons in favor of the results obtained: on one hand, the strongest results in the experiment were in terms of quality, a variable participants were not aware of; on the other, the combination in the game of incentives and moral hazard when costs are not to be borne resembles the alleged behavior of CEOs at banks during the recent financial crisis.

[249] Participants in the experimental sessions spent an average time of three hours to complete the tests on overconfidence and prospect theory, and the simulation game, instructions included.

CHAPTER 9. A BEHAVIORAL MODEL OF THE CREDIT CYCLE

9.1. INTRODUCTION

The purpose of the theoretical analysis in this chapter is to follow the second and third steps in the stepwise approach in Chapter 6 to determine how a duopoly of banks would compete to grant credit. The model starts from the assumption, backed by our findings in the experimental research in Chapters 7 and 8, that some banks in the industry might be biased in terms of overconfidence and excessive optimism —particularly during the upswing of the economic cycle.

Unsustainable credit and asset price booms are likely to occur in stable macroeconomic conditions (Borio and Shim, 2007), and excessive optimism and overconfidence might be plausible explanations to that evidence. Following this intuition, a recent line of research offers a few behavioral models of credit cycles. These include Keen (2011) on a monetary macroeconomic model of the financial instability hypothesis (Minsky, 1982a,b, 1992); Rötheli (2012a,b), who proposes a model of oligopolistic banking competition where a minority of boundedly rational banks are enough to aggravate the credit cycle; and Boz and Mendoza (2014), who provide a model on the effects of financial innovation and overconfidence to amplify the credit cycle. Some antecedents are Lewis (2010) and Leiser, Bourgeois-Gironde and Benita (2010), who trace some effects of social psychology on financial cycles, and Niu (2010), who offers some empirical evidence that banks managed by overconfident CEOs take more risk.

In this chapter we extend that literature with two developments. In the first one we examine how credit booms are fueled by the banking sector. To such purpose we follow the stepwise approach in Chapter 6 to analyze how a duopoly of a rational and a biased bank would compete to grant credit to the economy, whether herding strategies would appear, and whether limits of arbitrage in the industry are identifiable. We build a model of duopoly competition among banks to show that behavioral biases by participants in the industry explain how a credit bubble is fueled. According to it, biased banks would lead the industry and unbiased banks herd under conditions we derive, what generates a credit boom of loans of low quality. Finally, we describe the limits of arbitrage that are implicit in the model.

Our results are in line with Rötheli (2012a,b) and Boz and Mendoza (2014) in the sense that their models predict that overconfidence generates a bubble. However, our model provides a more intuitive interpretation of how bank competition may aggravate credit booms: overconfident banks always follow their priors while there is a rationale for rational banks to herd. This key finding emphasizes the potential pervasiveness of behavioral biases. In addition, the model suggests bank-based systems are less likely to be informationally efficient than market-based ones: first, the mere presence of a biased bank leads the banking sector to grant excess credit —this also supports Rötheli's (2012a) results that the amplifying effect of bounded rationality persists when only a fraction of banks are biased; besides, the limits of arbitrage that allow price inefficiencies to survive are implicit, as private banks have not an economic motivation to hedge credit markets given the assumptions in our model.

The second development of our model contributes to explain how the credit cycle is amplified due to banking competition. For such purpose, we first model the economic cycle following Rötheli (2012b) where boundedly rational banks overestimate probabilities of success during booms and underestimate them during recessions. Then, we extend the model to consider the effects of underconfidence and pessimism in the recessive periods of the credit cycle, in order to determine whether symmetry exists regarding the effects over and underconfidence induce in retail credit markets. We find pessimism would not be a powerful driver of credit cycles. Rather than that, our model supports it is euphoria during large upswings what seeds the next crunch. This disputes the alternative interpretation in models like Rötheli (2012a), where the interest rate decisions of a minority of boundedly rational banks induce the more rational competitors to aggravate the credit cycle during both booms and recessions. Other authors, like Boz and Mendoza (2014), also interpret pessimism has amplification effects on debt, but our opposite results are not comparable to theirs, because they assume all agents are boundedly rational and because they consider the effects of financial innovation on cycles.

Finally, we offer a dynamization of our model to provide further insight on how boundedly rational competition would amplify the credit cycle. We offer four additional insights. First, the effects are relevant particularly during upswings. Second, the conditions for a herding behavior to appear in both booms and recessions are determined. Third, only for high levels of pessimism some amplification effects over the cycle would be observed. However, in such case simply cut rates would be a powerful tool for economic authorities to soften the recession, in contradiction with episodes like the recent recession. Fourth, excessive optimism as a driver of a credit boom is shown to be a plausible explanation particularly the lower the quality of the niche markets.

In the remainder of this chapter we develop this model.[250] Section 9.2 formalizes the behavioral model of herding and limits of arbitrage in retail credit markets. In Section 9.3 we extend the model to consider the effects of pessimism and underconfidence. Then, Section 9.4 offers a dynamization of the model all over the boom-bust cycle. Finally, Section 9.5 concludes. The proof of the main results is relegated to an Appendix.

[250] In what follows we reproduce the original research where we developed this model. Thus, Section 9.2 reproduces an article published in Studies in Economics and Finance (Peón, Antelo and Calvo, 2015), whereas in Sections 9.3 and 9.4 we reproduce two excerpts from a manuscript in the second round of revision in a JCR ranked journal at the time of the writing of this thesis.

9.2. A BEHAVIORAL MODEL OF THE CREDIT BOOM[251]

We deal with an oligopolistic model of banking and focus only on the informational side of EMH to show that even in a world with no asymmetric information behavioral biases may explain why bank-based systems may still not be informationally efficient. To such purpose, assume the economy consists of the banking sector, savers and potential borrowers. Banks may be of two types, type A and type B, the first being an unbiased bank and the second a biased bank.[252] In particular, a bank of type B is boundedly rational in terms of excessive optimism (perhaps fostered by overconfidence too), so we often refer to it as an optimistic or overconfident bank. There are no agency problems between shareholders and managers, and no information asymmetries.

The only business banks run are taking deposits and granting loans. For tractability purposes, we assume the following: (i) deposits can only be invested in loans, i.e., there is no interbank market or rates are zero there, (ii) deposits are hold until maturity (banks face no liquidity restrictions, so no fraction of the deposits are hold as liquid reserves, R=0), (iii) the Central Bank requires no reserves, and (iv) bankruptcy effects are not considered. Banks receive deposits from savers, who have other investment alternatives that pay a competitive rate of return, r, $r\geq 0$. There is an unlimited source of deposits available, hence we assume that banks take the rate r as given and set a volume of deposits D^i, i=A,B, equal to the volume of loans they grant, as to finance them.[253] Banks are risk-neutral and compete in Cournot fashion by setting, independent and simultaneously, the volume of loans. The cost function of the banks, $C(D,L)$, where D stands for deposits and L for loans, is linear and is defined as $C(L)=cL$, $c>0$, given that they set a volume of loans equal to the volume of deposits.

In the market there are two types of borrowers, high-quality and low-quality borrowers. A high-quality customer, which is denoted by subscript h, is a client that fully repays a loan more likely than a low-quality client, which is referred by subscript l. Thus, banks are confronted with two downward sloping demand functions for loans, one for each type of borrower. We assume that both demands are the linear functions $L(r_h)=\alpha-\beta r_h$ and $L(r_l)=\alpha-\beta r_l$, being $\alpha>0$ and $\beta>0$. The (gross) rates of return on loans are r_h and r_l, respectively, with $r_l>r$ and $r_h>r$. Both banks are able, after a costless screening process, to correctly assign any new potential borrower to the type she belongs to. Each type of borrower is associated to a probability of success θ_h and θ_l, $0 < \theta_l < \theta_h < 1$, which are the probabilities that a loan

[251] Article forthcoming in Studies in Economics and Finance, Volume 32, 2015

[252] Obviously, this is a simplification of language: banks are neither biased nor unbiased; who may be biased are executives, employees, and procedures for decision-making inside those banks.

[253] When there are no liquidity restrictions and banks are not competing for deposits (given they are paying a competitive rate r and there is an unlimited amount of deposits available), there is no reason to accumulate (and pay interests for) a volume of deposits higher than necessary.

of each type is fully repaid, while whenever the borrower defaults the bank gets zero. Key to our model is the assumption of rational and overly optimistic banks in terms of these probabilities. Formally,

Assumption 1. $\theta_h^B = \theta_h^A$ and $\theta_l^B > \theta_l^A$.

That is, if a bank is of type A, then it observes the true probabilities of success given information available[254] of both types of borrowers; conversely, a bank of type B estimates an unbiased probability for high-quality borrowers, but a lower probability of default by low-quality borrowers than a bank of type A. Assumption 1 sets overestimation of probabilities of success by low-quality borrowers as the main driver of the model. From now on, we will use the notation $\theta_l^A \equiv \theta_l$ and $\theta_l^B \equiv \theta_l^O$ (superscript O denotes overconfident), being $0 < \theta_l < \theta_l^O < \theta_h < 1$.

Assumption 2. The parameters of the model are such they satisfy $\alpha > \dfrac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$.

Assumption 2 imposes a restriction on the demand size for loans. It states that the size of the market needs to be sufficiently large to guarantee that interest rates are well defined in equilibrium, meaning they are neither negative nor they exceed the maximum possible value α/β in the equilibrium.

Under this setup we analyze informational efficiency following the behavioral approach described in Chapter 6; namely, do banks behave rationally when granting credit to the economy? (subsection 9.2.1), may biased strategies be correlated across the banking industry? (subsection 9.2.2), and are there limits of arbitrage in the banking industry? (subsection 9.2.3).

9.2.1. Analysis of rationality

The goal of this section is to identify whether banks behave rational or biased and what would be the effects over credit aggregates. Consider the particular case of two banks competing in the economy. How would this duopoly be characterized if both banks are unbiased? And what if one of them or both are excessively optimistic? We model this market following the Monti–Klein approach of an oligopoly,[255] where the banks' decision variables are the volumes of loans, namely L_h in the niche formed by high-quality borrowers and L_l in the niche formed by low-quality borrowers. Banks analyze the borrowers' quality and decide how much credit to grant.

Having two banks in the industry, we may face three different situations: (i) both banks are unbiased; (ii) one bank is boundedly rational; or (iii) both banks are biased. Next, we examine the

---

[254] That is, banks correctly infer whether a borrower is of a good or a bad quality, where of course chances of default are higher for bad borrowers. However, we consider that, given information available, rational banks are able to correctly calibrate the probabilities of success of both good and bad borrowers; optimistic banks, instead, believe bad-borrowers' chance of success is higher than they should have rationally presumed.

[255] See Freixas and Rochet (1998) for a detailed description.

outcome of each one of them. First, if both banks are of type *A* (we refer to this as a rational duopoly), we have symmetric Cournot competitors solving the problem

$$\left.\begin{array}{l}\max E\,\Pi^i(L_h^i, L_l^i) = \theta_h \cdot r_h(L_h^i + L_h^{j*})L_h^i - (1-\theta_h)L_h^i + \theta_l \cdot r_l(L_l^i + L_l^{j*})L_l^i - (1-\theta_l)L_l^i - rD^i - C(D, L) \\ \text{s.t}: L_h^i + L_l^i = D^i\end{array}\right\} \quad (9.1)$$

where *i*,*j*=*A*,*B*; *i*≠*j*, and superscript * denotes equilibrium value. The solution of (9.1) renders

$$L_h^{A*} = L_h^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3\theta_h} \quad (9.2)$$

and

$$L_{l,rD}^{A*} = L_{l,rD}^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3\theta_l}, \quad (9.3)$$

where $L_{l,rD}^{i*}$ denotes the volume granted by each bank *i*, *i*=*A*,*B*, to low-quality borrowers in a rational duopoly market (denoted by subscripts *rD*). Finally, the corresponding clearing interest rates are

$$r_h^* = \frac{\alpha}{3\beta} + \frac{2(1+r+c-\theta_h)}{3\theta_h} \quad (9.4)$$

and

$$r_{l,rD}^* = \frac{\alpha}{3\beta} + \frac{2(1+r+c-\theta_l)}{3\theta_l}. \quad (9.5)$$

We may see that the decision problem for high and low-quality markets is separable; namely, L_h^* and L_l^* are independent. This makes that the relevant results will be found only in market niches where at least one bank is biased.

Second, what would happen if there is an asymmetric duopoly where one bank is unbiased in both markets (type *A*) and the other is biased when analyzing the probability of success of low-quality borrowers (type *B*)? Since markets are separable, volumes of loans and interest rates in the high-quality market are identical to the results above —see (9.2) and (9.4), respectively. By contrast, in the low-quality market we get

$$L_{l,aD}^{A*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3}\left(\frac{2}{\theta_l} - \frac{1}{\theta_l^O}\right) \quad (9.6)$$

and

$$L_{l,aD}^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3}\left(\frac{2}{\theta_l^O} - \frac{1}{\theta_l}\right), \quad (9.7)$$

where $L_{l,aD}^{i*}$ denotes the volume of loans provided by bank *i* to low-quality borrowers in an asymmetric duopoly (denoted by subscript *aD*). In this case, the interest rate for low-quality borrowers that clears the market is

$$r_{l,aD}^{*} = \frac{\alpha - 2\beta}{3\beta} + \frac{1+r+c}{3}\left(\frac{1}{\theta_l} + \frac{1}{\theta_l^O}\right). \tag{9.8}$$

Thus, the consequence of having a biased bank in the industry is that the rational bank reduces the amount of credit granted to low-quality borrowers[256] with respect to the situation in which there is no biased bank, while the boundedly rational bank chooses a larger volume. In fact, it may happen that a bank of type *A* ends up driven out of the market of low-quality borrowers. Setting $L_{l,aD}^{i*} = 0$ in (9.6) and solving for θ_l, we define the cut-off value θ_l^M

$$\theta_l^{\mathrm{M}} = \frac{2\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + \beta(1+r+c)}, \tag{9.9}$$

being $0 < \theta_l^M < 1$, for which a monopoly condition $\theta_l \leq \theta_l^M$ emerges. Thus, when $\theta_l > \theta_l^M$, the volume of credit that a bank of type *A* grants to low-quality borrowers is strictly non-negative; hence, the market becomes an asymmetric duopoly. Contrariwise, if $\theta_l \leq \theta_l^M$, there would be a monopoly formed by (the boundedly rational) bank *B*, which solves

$$\left.\begin{aligned} &\max E\,\Pi^B(L_h^B, L_l^B) = \theta_h \cdot r_h(L_h^B + L_h^{A*})L_h^B - (1-\theta_h)L_h^B + \theta_l^O \cdot r_l(L_l^B)L_l^B - (1-\theta_l^O)L_l^B - rD^B - C(D,L) \\ &\text{s.t}: L_h^B + L_l^B = D^B \end{aligned}\right\} \tag{9.10}$$

which affords

$$L_{l,M}^{*} = \frac{\alpha+\beta}{2} - \frac{\beta(1+r+c)}{2\theta_l^O} \tag{9.11}$$

as the volume of loans granted to low-quality borrowers (subscript *M* stands for monopoly). Consequently, the interest rate to be paid by the these borrowers when there is a monopoly by bank *B* in that niche would amount to

$$r_{l,M}^{*} = \frac{\alpha}{2\beta} + \frac{1+r+c-\theta_l^O}{2\theta_l^O}. \tag{9.12}$$

Finally, we may have a market where both banks are of type *B* (the so-called biased duopoly). They would be symmetric Cournot competitors solving a similar problem as in (9.1), but where the probability of success of low-quality borrowers is now replaced by θ_l^O. In this case, the level of loans

[256] Indeed, it is easy to see that the credit volume in (9.3) is larger than in (9.6).

granted in the high-quality market is that given in (9.2), whereas the interest rate these borrowers have to pay is that given in (9.4). In turn, for low-quality borrowers we have the volume of loans

$$L_{l,bD}^{A*} = L_{l,bD}^{B*} = \frac{\alpha + \beta}{3} - \frac{\beta(1 + r + c)}{3\theta_l^O} \tag{9.13}$$

granted by each bank and

$$r_{l,bD}^{*} = \frac{\alpha}{3\beta} + \frac{2(1 + r + c - \theta_l^O)}{3\theta_l^O} \tag{9.14}$$

as the interest rate to be paid by these borrowers in a biased duopoly (denoted by subscript *bD*). We can easily establish the following result.

Lemma 1. *The following holds as a function of* θ_l*:*

(i) *If* $\theta_l > \theta_l^M$*, then* $L_{l,bD}^{*} > L_{l,aD}^{*} > L_{l,rD}^{*}$.

(ii) *If* $\theta_l \leq \theta_l^M$*, then* $L_{l,bD}^{*} > L_{l,M}^{*} > L_{l,rD}^{*}$.

Proof. See Appendix.

Lemma 1 shows that either the biased or the asymmetric duopoly (or the monopoly when the monopoly condition holds) generate a credit boom in the low-quality market above what it would be informationally efficient, with the largest credit boom coming in a duopoly market where both banks follow the biased strategy.

9.2.2. Herd behavior

The goal of this section is to determine whether the biased strategies might be correlated across banks, even to the point that unbiased participants follow their biased competitors. To this end, we consider that the banking sector is formed by two banks, one is unbiased (bank *A*) and the other is biased (bank *B*). Assume for a while that the no-monopoly condition $\theta_l > \theta_l^M$ does hold. We would expect this market is described by (9.2), (9.6) and (9.7), with correspondent interest rates stated in (9.4) and (9.8), as we saw in subsection 9.2.1.

Consider now that banks are able to observe their competitor's estimated probabilities. Though each bank considers its own estimations as —by definition— unbiased, a key feature of the model is that, when banks of a different nature compete, they consider an *ex-ante* analysis of strategies to determine whether it is more profitable to them playing rational or biased (regardless of their true nature), given the possible alternatives the opposite bank may follow, and assuming that both banks move simultaneously. This may be summarized as the game in Table 9.1.

TABLE 9.1 – Possible market configurations of the low-quality niche

		BANK B plays	
		UNBIASED	**BIASED**
BANK A plays	**UNBIASED**	RATIONAL DUOPOLY (at the low-quality market)	ASYMMETRIC DUOPOLY (at the low-quality market)
	BIASED	INVERTED ASYM. DUOP (at the low-quality market)	BIASED DUOPOLY (at the low-quality market)

Source: Own elaboration

For instance, if bank A considers that bank B will follow its own priors (playing biased or optimistic), bank A compares whether it is better to determine how much credit to grant using its own probabilities (playing unbiased or rational, hence we have an asymmetric duopoly) or imitating the optimistic bank to share one half of the market in a biased duopoly. Considering all the alternatives, the possible market configurations are: a rational duopoly when both banks play unbiased (regardless of their true nature), a biased duopoly when both play biased, an asymmetric duopoly when they follow their own convictions, or an inverted asymmetric duopoly where bank B plays unbiased and bank A plays biased, both playing against their own true nature.[257]

The volumes of loans and interest rates of each possible market configuration would be those analyzed in subsection 9.2.1. Nonetheless, in order to determine the Nash equilibria concerning the market configuration, we must estimate the expected profits banks have in each possible scenario, but using their own priors θ_l (bank A) and θ_l^O (bank B), since those are the probabilities they truly observe. The following results are obtained.

Lemma 2. *Playing biased is a dominant strategy for bank B.*

Proof. See Appendix.

Lemma 2 leads to the following result.

Lemma 3. *Bank A herds whenever $\theta_l > \theta_l^T$, where* $\theta_l^{\mathrm{T}} = \dfrac{6\beta(1+r+c)\theta_l\theta_l^O}{(\alpha+\beta)\theta_l^O + \beta(1+r+c)(3\theta_l + 2\theta_l^O)}$.

Proof. See Appendix.

Lemma 3 shows that there may be market conditions where even unbiased participants would follow their biased competitors. In particular, there is a threshold bias $\theta_l^O - \theta_l^T$ such that when bank B is not too biased, bank A herds to grant credit as if it had biased expectations. When $\theta_l \leq \theta_l^M$, the no-

[257] Similar volumes of loans and interest rates apply when we have an inverted asymmetric duopoly, but with (9.6) applying to bank B (which now would play rational) and (9.7) applying to bank A (which now would play biased). Were this market a monopoly (i.e., when the no-monopoly condition is not satisfied) bank A would be the monopolist instead of bank B.

monopoly condition does not hold and the cut-off value becomes $\theta_l^{\mathrm{T}} = \dfrac{3\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + 2\beta(1+r+c)}$. We show in the Appendix that in this situation $\theta_l^T > \theta_l^M$, hence when the asymmetric market of low-quality borrowers is a monopoly formed by bank *B*, it always becomes the equilibrium (since bank *A* chooses to play rational).

Proposition 1. *If a rational and a biased bank compete, the following occurs in the niche of low-quality borrowers:*

(i) *When θ_l is sufficiently large as such $\theta_l^M < \theta_l^T < \theta_l$, a biased duopoly where bank A herds holds;*

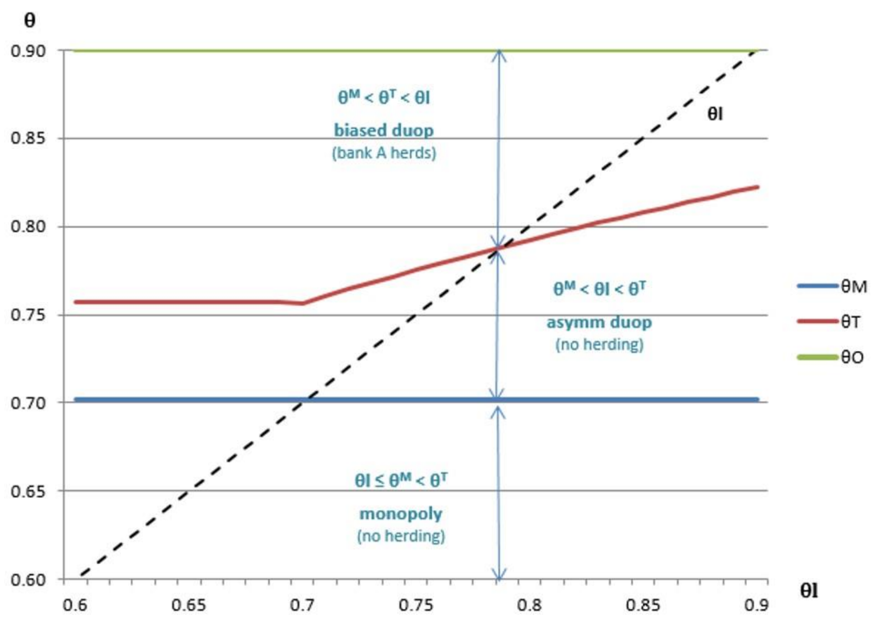
(ii) *When θ_l is moderate as such $\theta_l^M < \theta_l < \theta_l^T$, an asymmetric duopoly where both banks use their own prior assessments emerges;*

(iii) *When θ_l is sufficiently low as such $\theta_l \leq \theta_l^M$, a monopoly formed by the biased bank B holds.*

Proof. See Appendix.

Figure 9.1 below provides a graphic interpretation of Proposition 1, where θ_l^O has been set to be $\theta_l^O = 0.9$ and θ_l varies all along the dotted line.[258]

FIGURE 9.1 – Possible equilibrium configurations in the low-quality niche



Source: Own elaboration

[258] We have also considered r=0.1, c=0.05, and α=β=1 in this example.

We may note the kinked feature of θ_l^T (when $\theta_l \leq \theta_l^M$ the expression for θ_l^T in Lemma 3 simplifies to $\theta_l^{\mathrm{T}} = \dfrac{3\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + 2\beta(1+r+c)}$, insensitive to θ_l; hence horizontal). Since $\theta_l^T > \theta_l^M$ is satisfied, as the bias $\theta_l^O - \theta_l$ increases (as we move down the dotted line in Figure 9.2) we may have the three different possible market configurations of equilibrium. Namely, in this example, a biased duopoly emerges for $0.789 < \theta_l < 0.9$, an asymmetric duopoly for $0.702 < \theta_l < 0.789$ and a monopoly whenever $\theta_l \leq 0.702$.

Remark 1. *In all the three possible equilibrium market configurations a credit boom of loans of low quality at a lower-than-rational rate is generated, with the largest credit boom following when the unbiased bank herds. Further, this credit boom increases the welfare of low-quality borrowers.*

Proof. See Appendix.

A numerical example

Consider a base case of a duopolistic banking sector where the demand for loans of each type of borrowers are $L(r_h)$=1−r_h and $L(r_l)$=1−r_l, the cost function is $C(L)$=0.05·L for both banks, and the interest rate of deposits is r=0.1. In addition, assume that $\theta_h = 0.95$, $\theta_l = 0.7$ and $\theta_l^O = 0.75$. Then, the equilibrium values for credit volumes, interest rates and expected profits for each bank are summarized in the base model (case 1) of Table 9.2.

TABLE 9.2 – Case analysis

											high-quality		rational Duop		asymm. Duop		Monopoly		inverted Duop		invert. Monop		biased Duop			
Model	θ_h	θ_l	θ_l^O	α	β	r	c	A2	θ_l^M		A	B	A	B	A	B	A	B	A	B	A	B	A	B	θ_l^T	boom
										L	0.263	0.263	0.119	0.119	0.083	0.192	0	0.233	0.192	0.083	0.233	0	0.156	0.156		
1. Base	0.95	0.7	0.75	1	1	0.1	0.05	0.533	0.651	r	0.474		0.762		0.725		0.767		0.725		0.767		0.689			
										EΠ			0.0757	0.0862	0.0706	0.0935			0.0769	0.0777			0.0708	0.0839	0.698	30.7%
										L	0.263	0.263	0.119	0.119	0.051	0.256	0	0.281	0.256	0.051	0.281	0	0.188	0.188		
2. Base_asym	0.95	0.7	0.8	1	1	0.1	0.05	0.438	0.669	r	0.474		0.762		0.693		0.719		0.693		0.719		0.625			
										EΠ			0.0757	0.0967	0.0676	0.1182			0.0749	0.0761			0.0634	0.0939	0.719	28.8%
										L	0.263	0.263	0.119	0.119	-0.003	0.362	0	0.361	0.362	-0.003	0.361	0	0.241	0.241		
3. Base_monop	0.95	0.7	0.9	1	1	0.1	0.05	0.278	0.702	r	0.474		0.762		0.640		0.639		0.640		0.639		0.519			
										EΠ			0.0757	0.1177			0.0658	0.1832			0.0648	0.0658	0.0448	0.1179	0.757	51.7%
										L	1.596	1.596	1.452	1.452	1.416	1.525	0	2.233	1.525	1.416	2.233	0	1.489	1.489		
4. Demand (α)	0.95	0.7	0.75	5	1	0.1	0.05	0.533	0.305	r	1.807		2.095		2.059		2.767		2.059		2.767		2.022			
										EΠ			3.8979	4.1227	3.8246	4.1665			3.9332	4.0412			3.8589	4.0839	0.497	2.5%
										L	0.228	0.228	-0.048	-0.048	-0.117	0.092	0	0.033	0.092	-0.117	0.033	0	0.022	0.022		
5. Demand (β)	0.95	0.7	0.75	1	2	0.05	0.05	0.933	0.742	r	0.272		0.548		0.513		0.483		0.513		0.483		0.478			
										EΠ			0.0255	0.0218			0.0247	0.0251			0.0227	0.0247	0.0233	0.0249	0.73	∞
										L	0.175	0.175	0	0	-0.044	0.089	0	0.067	0.089	-0.044	0.067	0	0.044	0.044		
6. High-cost	0.95	0.7	0.75	1	1	0.1	0.3	0.867	0.724	r	0.649		1.000		0.956		0.933		0.956		0.933		0.911			
										EΠ			0.0292	0.0292			0.0292	0.0326			0.0261	0.0292	0.0265	0.0307	0.724	∞
										L	0.316	0.316	0.19	0.19	0.159	0.254	0	0.333	0.254	0.159	0.333	0	0.222	0.222		
7. No-cost	0.95	0.7	0.75	1	1	0	0	0.333	0.600	r	0.368		0.619		0.587		0.667		0.587		0.667		0.556			
										EΠ			0.1201	0.1356	0.1124	0.1431			0.1230	0.1250			0.1145	0.1318	0.677	16.7%

Source: Own elaboration

In the base case, Assumption 2 imposes a minimum market size α>0.533 for an equilibrium to exist. The no-monopoly condition requires $\theta_l > \theta_l^M = 0.651$, which is satisfied; hence, the four possible market configurations in the niche for low-quality borrowers are rational, asymmetric, inverted and biased duopolies (volumes and rates in the monopolies are shadowed since they would not apply here). We may know in advance which one will be the equilibrium by checking $\theta_l > \theta_l^T = 0.698$: bank A will herd to compete in a biased duopoly. One may easily check in Table I that would be indeed the Nash equilibrium, generating a credit boom of low-quality loans of a 30.7% (total volume 0.311 versus 0.238) at a lower rate (0.762 versus 0.689) compared to what a duopoly of unbiased banks would set.

Were bank B more biased, the herding condition would not be satisfied and bank A would choose to play unbiased in an asymmetric duopoly. That happens in the second case, denoted 'Base_asym', where we set $\theta_l^O = 0.8$. Were bank B more biased (case 3 'Base_monop', where we set $\theta_l^O = 0.9$) it may happen that the no-monopoly condition is not satisfied. In this third model we have $\theta_l < \theta_l^M = 0.702$; hence the monopoly becomes the equilibrium market structure. Finally, cases 4 to 7 analyze the effects of changes in demand (α and β) and cost (r and c) parameters of the model. We conclude that herding conditions are more likely to exist the larger the market size and the lower the costs. In any case, as long as θ_l^O is strictly larger than θ_l, bank B will find it profitable to play biased.

Therefore, we have shown that it is rational for a bank, under specific circumstances, to move out of the rational price for low-quality credit. Thus, a mix of overconfident and unbiased banks competing for loans generates a higher demand for (low-quality) loans that are provided at a lower-than-rational price, i.e. a credit boom may emerge that, eventually, might collapse.

9.2.3. Limits of arbitrage

In this final step we examine whether there are limits of arbitrage in the banking industry. In credit markets, arbitrage between close substitutes makes no sense from a micro perspective: since there are no securities, a bank observing other bank granting a loan that underestimates the creditor's risk would only be able to make profit out of arbitrage if it were possible to grant a new loan to a perfect substitute (other customer) and short-sell the former somehow. In addition, the risk assumed in a credit transaction cannot be offset with the reduction of credit granted to any other agent in the market. Therefore, hedging should be considered in retail credit markets only at a macro level: Are there market participants able to rectify the excess credit provided by the banking system during credit bubbles —the opposite with credit rationing— for their own profit?

However, the main drawback for arbitrage in the aggregate credit market to be performed by private agents refers to the impossibility for this strategy to be profitable. During credit booms, when optimistic banks are making money by giving credit to anyone who demands it, an arbitrageur should be willing not to win that *easy money* and lose market share. Rather than that, we have seen that whenever $\theta_l > \theta_l^T$ an unbiased bank will be willing to fuel the credit boom to low-quality borrowers. Besides, we should neither expect the rational banks to be willing to reduce the loans granted to high quality borrowers (in order to compensate in aggregate terms for the higher volume of credit they grant to low quality borrowers) because that would make them lose money, too. On the other hand, banks could also use deposits for arbitrage purposes, but only with similar results: during credit bubbles, arbitrageurs (commercial banks) might raise the interest rate paid on deposits to a higher rate $r+\delta$, $\delta>0$, forcing competitors to do the same. This way, the cost of funding rises and banks would impose more stringent conditions on credit: they would be willing to reduce deposits (hence loans) to optimize their expected profits. However this strategy is not profitable for bank A, since it could only be done by paying more on its existing deposits —hence reducing its expected profits. The following result can be stated.

Proposition 2. *In retail credit markets there would be no rationale for private banks to correct mispricing.*

The ultimate set of arguments for efficient markets is that, as long as there are a sufficient number of rational arbitrageurs making profit out of the mispricing (Fama, 1970), efficiency is guaranteed. Instead, our model suggests that in retail credit markets the only presence of a biased bank is a sufficient condition for a bubble to be generated. Arbitrage must be profitable at no risk or it does not work, but private banks will not have an economic motivation to hedge credit markets given the assumptions in our model. Furthermore, banks themselves could, rather than hedge the market, play a speculative role: the classic moral hazard problem that has been suggested to be a key factor in the recent crisis, especially by too-big-to-fail entities (Bernanke, 2010). Therefore, a key conclusion would be that limits of arbitrage suggest bank-based systems are less likely to be informationally efficient than market-based ones,[259] even when informational asymmetries don't exist or are easy to overcome.

9.3. THE EFFECTS OF UNDERCONFIDENCE AND CHANGES ALONG THE CYCLE[260]

In order to take our model to a dynamic setup, three theoretical elements are necessary. First, how a duopoly of banks would compete in a static setup when one of them is biased in terms of excessive optimism and overconfidence. Here we follow the analysis described in Section 9.2. Second, how the same duopoly would compete if the boundedly rational bank is biased instead in terms of pessimism

---

[259] Shleifer (2000) would agree in support of central banking: *"[I]t is easy to see how [fire sales] lead to chains of liquidations, and to financial distress of many market participants. When these market participants are financial intermediaries, they may curtail their lending to firms, thereby engendering a recession. (...) Financial panics can thus have severe real consequences. This model [Shleifer and Vishny, 1997] provides a potential justification for the Central Bank or another institution becoming the lender of last resort that can step in at the time of crisis and stop the chain of liquidations (Bagehot 1872, Kindleberger 1978). In this model, such intervention would improve the efficiency of financial markets. In a more general model, it can perhaps preserve the integrity of the financial system as well, and even prevent an economic rather than just a financial meltdown"* (p. 107).

[260] Excerpt from a manuscript in the second round of revision in a JCR ranked journal at the time of the writing of this thesis.

and underconfidence. This is analyzed in subsection 9.3.1. Third, we need to examine how optimism and pessimism evolve along the business cycle. Here we borrow Rötheli's (2012a,b) theoretical and empirical description of the stylized dynamics of credit risk assessment to model how boundedly rational expectations and rational expectations on probabilities of success change all over the business cycle. This is described in subsection 9.3.2 below.

9.3.1. Pessimism and underconfidence in recessive periods

We now examine the effects of pessimism during recessions. For clarity of exposition we will only highlight the main differences observed when the boundedly rational competitor is biased in terms of pessimism/underconfidence rather than excessive optimism. Thus, if in Section 9.2 we defined overconfidence as overestimation of probabilities of success —i.e., the probability that a loan is fully repaid— during the upswing of the business cycle, fed by excessive optimism, now underconfidence means underestimation of probabilities of success, fed by pessimism during the economic crises.

This way, rather than having unbiased (type A) and overconfident (type B) banks, now we have an unbiased and an underconfident bank. The simplest way to tackle this is to note that we defined unbiased and overconfident banks in terms of bad borrowers' probabilities of success, $\theta_l^O > \theta_l$, that now change to $\theta_l^U < \theta_l$ (superscript U stands for underconfidence). Hence, assumptions 1 and 2 become

Assumption 1a. $\theta_h^B = \theta_h^A$, $\theta_l^B > \theta_l^A$

and, if θ_l^A is labelled as θ_l^U and θ_l^B as θ_l, it follows that $0 < \theta_l^U < \theta_l < \theta_h < 1$.

Assumption 2a. The parameters of the model are such they satisfy $\alpha > \dfrac{\beta(1+r+c-\theta_l)}{\theta_l}$.

Assumption 1a sets underestimation of probabilities of success as a key factor, while Assumption 2a may be proved to be the condition that ensures the size of the market is large enough to guarantee interest rates are well defined in the possible equilibria. Hence, we may go back and simply replace θ_l^O by θ_l and θ_l by θ_l^U in all formulae, such that notation A refers now to the underconfident bank, and notation B to the unbiased bank. This way, no additional calculations are required.

The most important finding is that it is now the unbiased player who leads the market. On one hand, playing rational is a dominant strategy for the unbiased bank B, as it comes from a symmetrical interpretation of the results above. On the other, a condition for the pessimistic bank to herd depends on a threshold bias $\theta_l - \theta_l^{UT}$, where

$$\theta_l^{UT} = \frac{6\beta(1+r+c)\theta_l\,\theta_l^U}{(\alpha+\beta)\theta_l\,\theta_l^U + \beta(1+r+c)(3\theta_l^U + 2\theta_l)} \tag{9.15}$$

such that when bank A is not too pessimistic (θ_l^U above θ_l^{UT} for a given θ_l) it herds to grant credit as if it had rational expectations. This herding condition would not apply when the no-monopoly condition $\theta_l^U > \theta_l^{UM}$ is not satisfied, where the cut-off value θ_l^{UM} is now defined as

$$\theta_l^U > \theta_l^{UM} = \frac{2\beta(1+r+c)\theta_l}{(\alpha+\beta)\theta_l + \beta(1+r+c)} \qquad (9.16)$$

This way, whenever the possible asymmetric market is a monopoly by the rational bank B, bank A chooses not to herd and the monopoly becomes the equilibrium. Consequently, there are also three possible equilibria in a recessive market: a rational duopoly, an asymmetric duopoly where both banks follow their own priors, and a monopoly by the unbiased bank B (when the no-monopoly condition does not hold). This result may be recorded as follows.

Proposition 3. *Pessimism is not as pervasive as excessive optimism.*

When rational and overoptimistic banks compete, the biased bank drives the industry and a credit boom of loans at a lower-than-rational rate is generated, as we saw in Section 9.2. On the contrary, when boundedly rational banks are bounded in terms of pessimism (underestimation of probabilities of success), rational banks lead the market. Pessimism might only partially explain the *credit crunch*, since the unbiased bank would never herd.

We find this result appealing for two reasons. First, we offer an alternative interpretation to Rötheli (2012a) for recessive markets. He suggests the cycle is amplified by boundedly rational behavior on both booms and recessions. We on the contrary predict pessimism is not a powerful driver. Second, our model predicts it is the euphoric economy developed during large upswings what seeds the fragility of the industry during the forthcoming recession. Put it other words, it would make sense to say financial crises are seeded during upturns, with excessive optimism driving markets, while credit rationing during recessions would be a consequence of past excesses (increased non-performing loans, undercapitalization, bank defaults, etc.) rather than a situation where banks are in good shape but cut down credit because of an excessive prudence.[261]

9.3.2. Dynamics of credit risk assessment

We are now in need of examining how optimism and pessimism evolve along the business cycle. Here we borrow from Rötheli's (2012a,b) setup, who shows how risk attitudes often change along the economic cycle. Rötheli (2012b) investigates the dynamics of banks' expectations as a mechanism that can give rise to inefficient lending cycles. Bayesian learning and the experience structure of banks could influence the loan-loss expectations and, therefore, the economic cycle. Following Rötheli (2012a), *"a model of boundedly rational credit risk assessment can be built based on the assumption that bankers have*

[261] This intuition was in Rötheli (2012b) when he agrees *"excesses in lending during good times eventually, when projects fail and creditors default, bring about a financial crisis and a downturn in economic activity"* (p. 731).

a limited experience span and thus, in their Bayesian learning, overestimate the risk of default in recessions and underestimate this risk as the upswing continues for several years (p. 2).[262]

Rötheli (2012b) empirically calibrates the transition probabilities of the Markov chain process that governs the business cycle probabilities using data from the U.S. economy. He looks at a stationary economy that can be either on 'good times' with a low level of loan losses or 'bad times' with a high level of loan losses. The transition between these two states follows a Markov chain with probabilities p (good times follow good times), q (bad times follow bad times), $1-p$ (good times are followed by bad times) and $1-q$ (bad times are followed by good times).

Bankers form their default rate expectations on the correct assumption that the state of the economy follows a Markov process, but they do not know the objective transition probabilities of this stochastic process. Instead, Rötheli (2012b) assumes that they look back in time and estimate these probabilities through a Bayesian estimate of probabilities p and q by using a limited historical data sample. It is this limitation of the memory (or experience) span that makes bankers' behavior boundedly rational. It is worth to note here that Rötheli (2012a,b) works his model out of an interpretation similar to Minsky's financial instability hypothesis that the high risk aversion in the beginning of the upswing is consequence of the memory of a recent financial failure, while risk aversion starts to decline as things gradually improve in the short term (Keen, 2011).

According to his empirical estimations, credit defaults in recessions in the U.S. are about three times higher than during upswings, the average duration of a cycle is 24 quarters (70 months), with the average recession lasting 4 quarters (11 months) and the average expansion 20 quarters (59 months). Rötheli (2012a) summarizes the stylized dynamics of credit risk assessment as follows. On one hand, rationally assessed credit default risk (probability of success) rises (falls) during recession and falls (rises) during the upswing. On the other, during the recession and the early stages of the upswing boundedly rational risk assessment is overly pessimistic, while during the later stages of the upswing boundedly rational banks form an overly optimistic assessment of credit risk. Based on these observations, Rötheli (2012a) replicates the paths derived from the simulations with Bayesian learning as described by

$$d_t^{BRE} = d_t^{RE} + 0.677\left(d_t^{RE} - \bar{d}\right) \tag{9.17}$$

and

$$d_t^{RE} = d_{t-1}^{RE} + 0.81\left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.06\left(d_{t-1}^{RE} - \bar{d}\right) - 9\times10^8\left(d_{t-1}^{RE} - \bar{d}\right)^4 \ , \tag{9.18}$$

[262] Nonetheless, the assumption that recessions drive banking practices is questionable, since it might be very well the other way round (e.g. a single, but decisive event á la Lehman leads banks to contract credit leading to fall in the prices of collaterals).

where d_t^{BRE}, d_t^{RE} and $\bar{d}$ stand for boundedly rational default expectations, rational default expectations, and average default over the cycle, respectively.

9.4. A DYNAMIC MODEL OF THE CREDIT CYCLE[263]

Here we extend our model to a dynamic setup. We proceed in two stages. First, we project different paths for the unbiased and boundedly rational (both overly optimistic and pessimistic) expected probabilities of success along the economic cycle. Then, introducing those projections in our model, we solve for volumes in equilibrium. For simplicity and a better understanding of the results, we work with particular demand and cost functions that will be given below. With the aim of highlighting different market configurations that might result from this analysis, we will provide two different examples. They are detailed in subsections 9.4.1 and 9.4.2.

We project the dynamics of θ_l, θ_l^O and θ_l^U following Rötheli (2012a,b) in spirit. Two remarks about (9.17) and (9.18) are in order. First, the empirically estimated bias suggests excessive optimism and pessimism amplify the cycle by two thirds (0.677) above and below the average default rate. This gives us a good benchmark for the examples provided below. Second, Eq. (9.18) fits the stylized features of the empirical findings in Rötheli (2012b) where the default rate in good times would be 0.7345% and in bad times 2.6365%. However, when trying to replicate different default rates, different estimations should be used.[264] We solve this below by providing alternative stylized estimations of the dynamics of θ_l, θ_l^O and θ_l^U that satisfy the average duration of a cycle, the about three times higher default rates in recession, and the dynamics of credit risk assessment as predicted by Rötheli.

9.4.1. Standard scenario: Credit boom by a biased duopoly

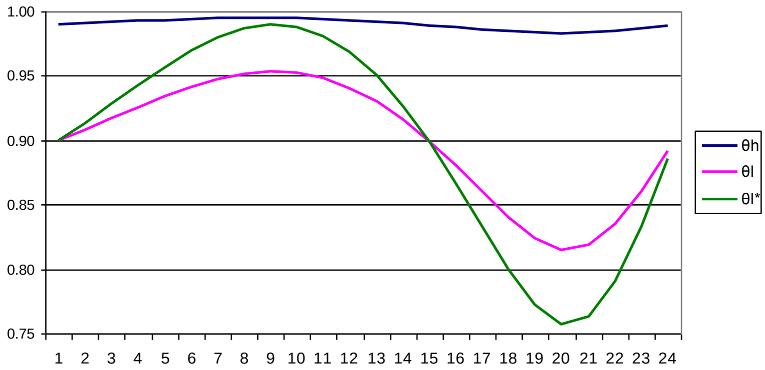
Figure 9.2 describes the paths probabilities θ_h, θ_l and θ_l^* (which denotes the biased probabilities θ_l^O or θ_l^U depending on the cycle phase) would follow in this first example. We consider an average default rate of 1% for high-quality borrowers ($\theta_h = 0.99$), an average default rate of 10% for low-quality borrowers ($\theta_l = 0.90$), and boundedly rational default expectations described as in (9.17).[265]

263 Excerpt from a manuscript in the second round of revision in a JCR ranked journal at the time of the writing of this thesis.

264 Note Rötheli (2012b) estimates the empirically observed default rates for the whole credit market in the US. However, in our model we separate different niche markets according to borrower qualities. Given this, we may be interested in estimating the paths for virtually any probabilities θ_h, θ_l , θ_l^O and θ_l^U in the range [0,1].

265 Here we stylized rational default expectation as $d_t^{RE} = d_{t-1}^{RE} + 1.1\left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.05\left(d_{t-1}^{RE} - \bar{d}\right) - 1000\left(d_{t-1}^{RE} - \bar{d}\right)^3 - 100000\left(d_{t-1}^{RE} - \bar{d}\right)^4$, where $\theta_h = 1 - d_t^{RE}$, and $d_t^{RE} = d_{t-1}^{RE} + 1.13\left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.056\left(d_{t-1}^{RE} - \bar{d}\right) - 5.6\left(d_{t-1}^{RE} - \bar{d}\right)^3 - 100\left(d_{t-1}^{RE} - \bar{d}\right)^4$, for $\theta_l = 1 - d_t^{RE}$.

FIGURE 9.2 – Probabilities of success, from quarters 1 to 24, in the first example

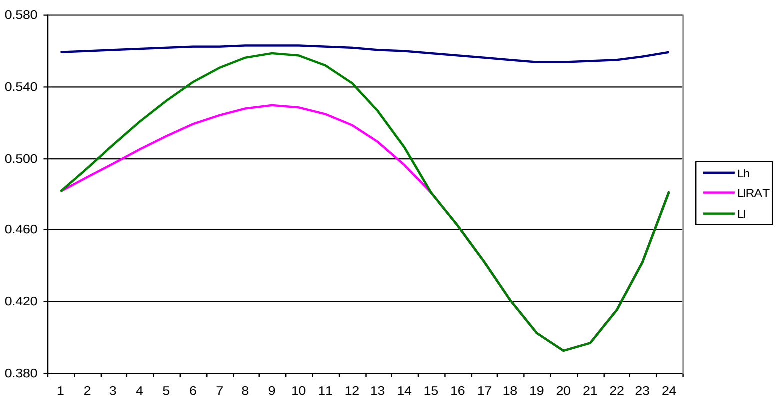


Source: Own elaboration

We may see in Figure 9.2 how unbiased probabilities θ_h and θ_l fall during recessions and rise during upswings, as to replicate a credit cycle of 24 quarters where credit default rates in recessions would be about three times higher than during upswings, as empirically observed. Besides, the biased probability θ_l^* increasingly deviates from the rational estimation θ_l, such that during good times boundedly rational risk assessment is overly optimistic, while during the recession and the early stages of the upswing a biased bank would make a pessimistic assessment of credit risk.

Consider this numerical example. The demand for loans are L(r_h) = 1 – r_h, and L(r_l) = 1 – r_l, for high and low-quality borrowers, the cost function of both banks is C(L) = 0.05 · L, and the interest rate of deposits amounts to r = 0.1.[266] Introducing the projected probabilities θ_h, θ_l and θ_l^* in our model, and solving for the volumes in equilibrium along the cycle, the paths depicted in Figure 9.3 are obtained.

FIGURE 9.3 – Loan volumes in a credit boom generated by a biased duopoly



Source: Own elaboration

[266] The interest rate on deposits of 0.1 we have set is clearly high. This deserves an explanation. First, we are opportunely using a high rate in order to emphasize the effects that can be observed when the monetary authorities reduce the cost of money to a large extent (see subsection 9.4.2). Second, no matter the choice it does not affect the generality of the results: the interest rate of deposits always appears in all credit volumes and interest rates of all possible market outcomes (see Table 1) in terms of the kind (1+r+c). This way, in the example we could set instead r = 0.05 and c = 0.1, for instance, and no results would change.

We may see how, during good times, loan volumes granted increasingly deviate from the volumes a duopoly of unbiased banks would grant. This occurs because the threshold bias $\theta_l^O - \theta_l^T$ determined in Lemma 3 is never exceeded, so the rational bank follows the biased during the optimistic phase —the equilibrium market here is a biased duopoly. During bad times, the bias $\theta_l - \theta_l^U$ determined in Eq. (9.15) is always narrow enough for the pessimistic bank to herd, so the equilibrium market is a rational duopoly. Finally, the market of high-quality borrowers follows the regular trend as in this model the decision problem between high- and low-quality markets is separable, with both banks having unbiased expectations for this type of customers. This example features how a standard credit market would most often behave. To see why, we must first be aware of the following lemma.

Lemma 4*. The bias required for a bank not to follow the leader is the larger*

(i) *the larger the size of the market, α;*

(ii) *the lower the marginal cost of the bank;*

(iii) *the lower (higher) the true probability of success θ_l during optimistic (pessimistic) times.*

Proof. See Appendix.

Lemma 4 gives a clue on why, given the assumed values of the numerical example for costs (c = 0.05, *r* = 0.1), market size and a bias coefficient of 0.677, the value $\theta_l^O = 0.9$ is too large to yield a monopoly. We may change the parameters to get alternative market configurations, but we will face two problems. First, we know from Assumptions 2 and 2a that the higher the costs *c* and *r*, the minimum market size required for interest rates to be well-defined also increases. Second, we have seen that the empirical research by Rötheli (2012b) evidences average default rates about 1% and optimism and pessimism amplifying the cycle by a coefficient of 0.677 as we assumed. Therefore, scenarios with larger market sizes, higher probabilities of success and bounded rationality coefficients about those empirically observed by Rötheli (2012a,b) will yield the larger credit booms during good times and rational duopolies during recessions (i.e., no effects of underconfidence). For alternative market configurations to arise, market sizes must be narrower (and we are bounded here), the qualities of the niche markets lower, and bounded rationality coefficients must be much larger than empirically observed. This is illustrated in the next example.

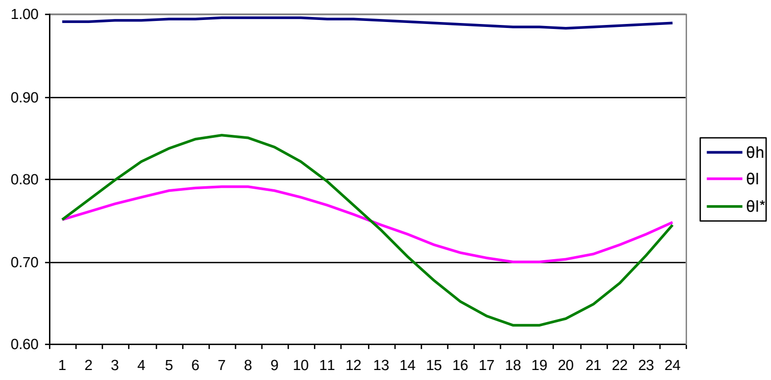
9.4.2. A stressed scenario

Consider now a second numerical example by assuming an average default rate of 1 percent for high quality borrowers ($\theta_h = 0.99$), of 25 percent for low-quality borrowers ($\theta_l = 0.75$) and a boundedly rational default expectations described as:

$$d_t^{BRE} = d_t^{RE} + 1.5\left(d_t^{RE} - \bar{d}\right). \tag{9.19}$$

That is, in this second example we have more than doubled the effects of excessive pessimism and optimism. Figure 9.4 describes the paths probabilities would follow in this case.[267]

FIGURE 9.4 – Probabilities of success, from quarters 1 to 24, in the second example



Source: Own elaboration

The interpretation of Figure 9.4 would be similar to that of Figure 9.2, but where now default rates in the low-quality market are much higher and where the deviation of boundedly rational probabilities with respect to the unbiased estimation is also much larger.

Finally, consider this stressed scenario to be characterized also by the cost function C (L)= 0.15 · *L* for both banks and the interest rate of deposits *r* = 0.1. In this case, the minimum market size for interest rates to be well defined would be α = 0.67; hence we cannot reduce the market size really much. To illustrate, we set demand for loans L(r_h) = 0.85 – r_h and L(r_l) = 0.85 – r_l. Introducing the projected θ_h, θ_l and θ_l^* in the model, and solving for the optimal volumes of loans in equilibrium along the cycle, the amount granted to low-quality borrowers depicted in Figure 9.5 holds.

We may see how, under this stressed scenario, market dynamics would be quite erratic. Volumes granted during the upswing rapidly deviate from the volumes a duopoly of rational banks would grant because of the larger effects of bounded rationality assumed in this example. Then, when the threshold bias $\theta_l^O - \theta_l^T$ is exceeded —which here occurs in quarter 5— the rational bank chooses not to keep on herding. Volumes fall as the market becomes an asymmetric duopoly, until in later in the downturn the bias falls again below the threshold level and the rational bank chooses to herd once again (quarter 11).

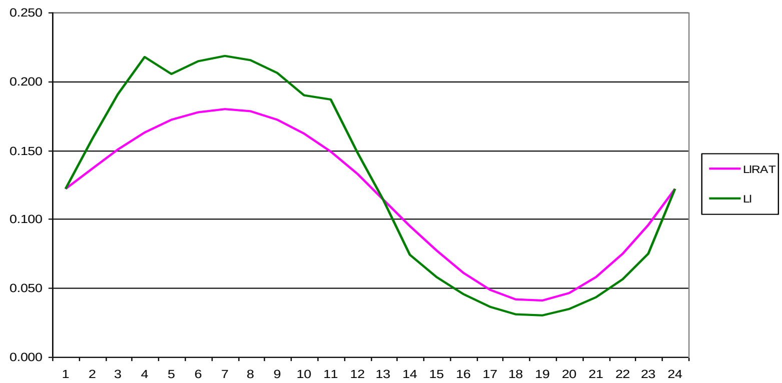
In the second phase, the biased bank rapidly changes its mood from optimistic to pessimistic as the recession hits. The rational bank now guides the market, which is now a rational duopoly only in quarter 13, an asymmetric duopoly in quarter 14, and a monopoly by the rational bank afterwards.[268] Volumes granted are close to zero, as these stressed conditions are close to qualities and market sizes

[267] Rational default expectations for low-quality borrowers have been stylized here as following the process $d_t^{RE} = d_{t-1}^{RE} + 1.04\left(d_{t-1}^{RE} - d_{t-2}^{RE}\right) - 0.075\left(d_{t-1}^{RE} - \bar{d}\right)$, for $\theta_l = 1 - d_t^{RE}$.

[268] The no-monopoly condition is not satisfied during most part of the downturn, from quarters 15 to 22.

that would make this type of borrowers not profitable for a rational lender. Hence, the credit crunch observed is of small size.

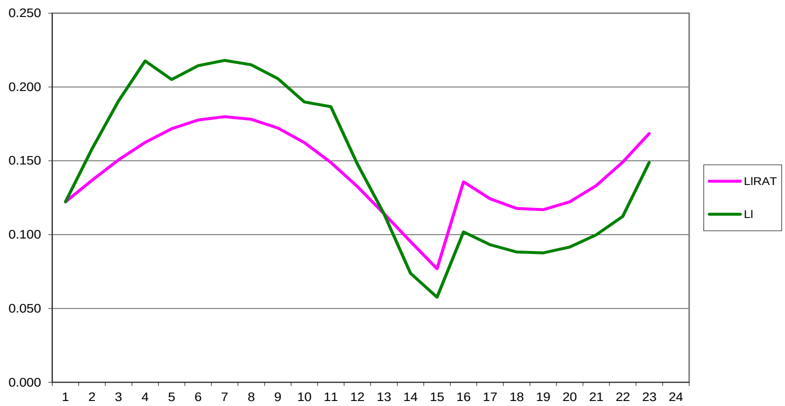
FIGURE 9.5 – Loan volumes in a stressed scenario



Source: Own elaboration

The dynamization of the model shows further evidence of the finding stated in Proposition 3. On one hand, excessive optimism may be a good explanation for the credit boom. The model predicts an erratic behavior for markets only under extreme conditions (low quality niches, small markets, and bounded rationality larger than empirically observed). On the other, excessive pessimism performs worse as an explanation for the credit crunch; only for high levels of pessimism some amplification effects over the cycle would be observed: the biased bank would not herd and the equilibrium would be a monopoly of the rational bank. An additional evidence of this second fact is illustrated in Figure 9.6.

FIGURE 9.6 – Monetary policy would end a recession



Source: Own elaboration

Figure 9.6 illustrates that not only the conditions for pessimism to have amplification effects over the cycle and a herding behavior not to appear would be quite extreme, but in such case economic authorities would have a powerful tool to soften the recession: relaxing monetary conditions. Assume that, in quarter 16, authorities try to help solving the crisis by reducing the cost of money. Now banks may finance at r = 0.02 rather than 0.1. Though the equilibrium in this stressed scenario would still be a monopoly by the rational bank, the market recovery is appreciable. However, this contradicts the empirical evidence these days where central banks all over the world —and particularly in the Euro zone— are facing strong difficulties to solve the credit crunch (see Eichengreen, Prasad and Rajan, 2011, for a discussion on the drawbacks of central banking).

Proposition 4. *Low-quality niche markets are more exposed to potential pervasive effects of bounded rationality on credit markets.*

Our behavioral explanation of the credit cycle suggests it is excessive optimism what drives the boom and generates the conditions for the crunch. However, on one hand Lemma 4(iii) shows that, for optimistic markets, the lower θ_l the higher the required bias for an unbiased bank not to herd. On the other, probabilities are bounded to [0, 1]. Hence, there is a cap for the pervasive effects during optimistic times: the closer probability θ_l is to 1, the lower the potential damage of bounded rationality.

9.5. CONCLUSIONS

The theoretical model we introduced follows the behavioral approach in three steps described in Chapter 6 to show excessive optimism by participants in the banking sector suffices to explain credit bubbles. We built a model of duopoly competition among banks to show how a rational bank would herd to follow the biased one. Then we compared the effects of optimism and pessimism, and offered a dynamization of the model to determine how the credit cycle is amplified, as well as we when and where (particularly, in which market niches) effects are expected to be more pervasive.

Five are the main results we obtain. First, overconfident banks always follow their priors and lead the industry, while rational banks herd under some conditions we derive. In particular, we show that there is a threshold bias such that when the biased bank is not too biased, the rational bank herds to grant credit as if it had biased expectations.

Second, a credit boom of loans of low quality at a lower-than-rational rate is generated in all possible equilibrium market configurations that may emerge. Any of such booms are welfare increasing for low-quality borrowers, while for high-quality borrowers there are no welfare effects.

Third, there would be no incentives for rational banks to correct the misallocations of their biased competitors. Limits of arbitrage suggest bank-based systems are less likely to be informationally efficient than market based ones. Informational efficiency, therefore, would rely solely on authorities.

Fourth, we find pessimism is not a powerful driver of credit cycles: during recessions, rational banks lead the market. Pessimism might only partially explain the *credit crunch*, as unbiased banks are not predicted to herd in any case. Consequently, the model predicts it would make sense to say financial crises are seeded during upturns, with excessive optimism driving markets, while the credit rationing observed during recessions would be a consequence of past excesses (increasing volume of non-performing loans, banks being under-capitalizated, defaults, etc.) rather than a situation where banks cut down credit because of an excessive prudence.

Finally, the fifth finding suggests that bounded rationality is expected to be more pervasive the lower the quality of the niche markets, since it is excessive optimism what drives the boom and, for optimistic markets, the lower the probability of loan repayment, θ_l , the higher the required bias for an unbiased bank not to herd.[269]

We are aware of the limitations of our model. For example, there are no financial systems that are solely bank-based or market-based. In addition, we would need a holistic view of the financial system and its links to macroeconomy (Borio and Shim, 2007), considering the effects of informational asymmetries and adverse selection. The model is a simple one to describe how banks would compete and the effects behavioral biases among the industry could induce. Further extensions should try to overcome this simplicity by considering the effects of informational asymmetries and adverse selection, alternative models of banking competition, the effects of bankruptcy costs, etc. Finally, another limitation of the model relies on the fact that it does not offer an endogenous explanation of the economic cycle. Rather than that, we take an exogenous (empirically observed) economic cycle to determine what the effects of over and underconfidence would be. Further extensions of the model might introduce complementary explanatory variables for the optimism of the banking sector (e.g. collaterals, total amount of debt, past bankruptcies) besides the overall economic development and their rival agents' behavior to endogenize the cyclical behavior of the economy with this setup.

In spite of these limitations, our work may be a relevant contribution to the literature in two aspects. First, we introduce an alternative approach to analyze informational efficiency in the banking industry that, to the best of our knowledge, had not been raised so far. Second, our model shows how behavioral biases might guide retail credit markets and why limits of arbitrage would be more pervasive in bank-based financial systems than in market-based ones. This is, we believe, an important contribution to the current debate on macroprudential regulation.

[269] As a consequence of having assumed linear cost functions, markets are separable and no externalities are expected in niche markets where all banks are rational. This also validates our assumption, for tractability purposes, that different niche markets have identical demand functions. However, these results no longer hold if we assume convex costs. On one hand, externalities of bounded rationality on markets where all participants are rational would appear. On the other, a further analysis of these externalities would require, nonetheless, to consider different demand functions for borrowers of a different nature.

SUMMARY OF RESULTS

The object of study in this thesis was the efficiency of bank-based financial systems when granting credit to the economy, with the aim of testing the informational efficiency of retail credit markets through a behavioral approach. The research we offered has succeeded, overall, to set an alternative way to implement such efficiency test, and to provide both an experimental evidence and theoretical rationale for behavioral biases to help explain credit booms. In what follows we summarize the main results of our theoretical and experimental research.

In Chapter 6 we introduced a behavioral framework to analyze the informational efficiency in retail credit markets, and provided a research agenda with various alternatives to test it in the future. The goal was to set an alternative way to analyze the informational efficiency of bank-based systems. The EMH by Fama (1970) described in Chapter 2, being the classic approach to examine efficiency in market-based systems, requires markets to be fully competitive and information available to all market participants. However, bank-based systems may not satisfy those conditions, as they are often characterized by imperfect competition and asymmetric information. Some alternatives that emerged to provide an interpretation of what determines how much credit banks should grant to borrowers were reviewed in Chapter 1. Now, in Chapter 6 we discussed how to extend the EMH to bank-based financial systems based on a behavioral approach. The main conclusions are in order.

1. Any analysis of the efficiency in bank-based financial systems must focus on the informational side of EMH, since allocative and operational efficiencies may not hold. This analysis is still of interest since, once we depart from a neo-classical equilibrium, markets may be informationally efficient yet allocatively inefficient (Bouchaud, Farmer and Lillo, 2008). Thus, the behavioral approach we introduce aims to provide a complementary element of analysis: even in a world with no asymmetric information, behavioral biases might explain why bank-based systems may still not be informationally efficient.

2. We argued that the extension of the EMH to bank-based systems makes no sense from a micro point of view (on a borrower-by-borrower basis). Macro efficiency must be analyzed instead, interpreted as how banks, in face of new information, change their credit policies —likewise the information theories described in Chapter 1. Such policies may be described in terms of prices, volumes and costs —likewise the efficiency measures outlined in Chapter 1, too. However, a major drawback for such alternative to be implemented is that prices, volumes

and costs define a bank's commercial strategy, hence they depend on non-directly observable information.

3. At this point, a behavioral approach based on Shleifer (2000) could be a feasible and testable alternative for retail credit markets. The approach, described for financial markets in Chapter 2, may be adapted to retail credit markets as follows. We may analyze changes in credit policies and whether through banking intermediation information is transmitted efficiently in the EMH sense in three steps. First, whether CEOs and employees in the industry exhibit beliefs that, based on heuristics and bounded rationality, could conform a market sentiment. Second, whether market sentiment could exhibit trends or predictable patterns. Third, whether there are limits of arbitrage in retail credit markets.

4. Chapter 6 ended with a research agenda to suggest various ways the stepwise approach might be empirically tested, following the taxonomy of biases and anomalies provided in Chapter 4. Then, in the last chapters of the thesis we developed a formal implementation of the stepwise approach. In particular, the first step is analyzed through an experimental research described in Chapters 7 and 8, while steps two and three are analyzed through a theoretical model of banking competition described in Chapter 9.

Chapter 7 described the behavioral tests we performed in an experimental setting to obtain a basic profile of each respondent's risk attitudes and level of confidence. We firstly introduced a set of tests to elicit the three measures of overconfidence as well as the complete set of parameters of value and weighting functions in prospect theory. Then, we organized a series of sessions where 126 students participated in an experiment that was divided in two parts. In the first part, they completed the tests to measure their individual levels of confidence and risk profile. The second part was the experimental implementation of a simulation game —described in Chapter 8. Finally, we confirmed the tests were broadly efficient to replicate the standard measures in the literature. The results obtained are in order:

5. With four trivia similar to those by Moore and Healy (2008) we obtain satisfactory results to obtain individual measures of overestimation and overplacement.

6. A test of fifteen questions revealed effective as well to replicate the main findings of prospect theory, considering the properties of the value and weighting functions, the fourfold pattern of risk attitudes, iteration and fitting errors, and anomalies at the individual level.

7. Our test for overprecision, instead, revealed incomplete to obtain estimations that are stable for different refinement methods. Having more questions per domain revealed necessary.

8. We also contributed with additional evidence about how gender, education and skills in finance affect overconfidence and risk aversion. In particular, the experimental analysis of all measures of overconfidence and prospect theory using the same group of respondents is

something that, to the best of our knowledge, was not done before. This allowed us to provide new insight on the relationship between these two relevant areas in the behavioral literature.

Chapter 8 introduced then a business simulation game devised to replicate the basics of the decision-making process of a bank granting credit to its customers under conditions of uncertainty and risk. This help us to tes the relationship between the participants' behavioral profile in Chapter 7 and their credit policies in the game. Several hypotheses about the effects of risk seeking, loss aversion and overconfidence were tested. In what follows we summarize the main results obtained:

9. We obtained extensive evidence that aggressive behavioral profiles —defined as high levels of overconfidence and risk seeking— are correlated to riskier credit strategies, particularly in terms of providing credit to low-quality customers at a lower rate. We did not find a single piece of evidence in the contrary direction, neither we were able to trace evidence that loss aversion had any effects on credit policies implemented.
10. The game design helped to reveal some results: participants were always given information in terms of confidence intervals and probabilities of default, and the results suggest that higher overprecision and risk seeking for gains (mostly attributable to probability weighting) foster lower prices, higher volumes of credit, and reduce quality. The most consistent result was distortion of probabilities fostering lower loan prices to low-quality customers.
11. The effects over credit quality were also the most relevant in terms of the external validity of the results. Participants knew their strategies were to be measured and scrutinized in terms of credit prices and volumes —hence their strategies might particularly be affected by a strategic behavior. However, they were not aware that their behavior in terms of quality was also tested (Levitt and List, 2007). This is good news, since key results in the experiment were the effects of overprecision and probability distortion over quality performence.

Nonetheless, we must be aware that the experiment has some limitations as well, which ought to be considered in future replications. They follow in order.

12. First, the results can only be considered robust if similar effects were observed for different individual measures of overconfidence and prospect theory obtained through other tests and elicitation methods available —cumulative prospect theory, non-parametric methods, etc.
13. Second, a strong result was in terms of the effects of overprecision, but in Chapter 7 we found that the overprecision measures were unstable at the individual level for different refinement methods. Thus, the validity of the results depend on future re-tests with enhanced methods.
14. Finally, the incentives in the game and the absence of penalties for excessive risk taking might have biased the results. This is a common drawback in any experimental research, and future versions of this game should try to solve it. Notwithstanding, we argue two reasons in favor

of the results obtained: on one hand, the strongest results in the experiment were in terms of quality, a variable participants were not aware of; on the other, the combination in the game of incentives and moral hazard when costs are not to be borne resembles the alleged behavior of CEOs at banks during the recent financial crisis.

Finally, Chapter 9 was devoted to provide a theoretical model of the credit cycle that shows how rational banks would herd to follow their biased competitors to grant excess credit during economic upswings. The theoretical model introduced follows the behavioral approach in three steps described in Chapter 6 to show excessive optimism by participants in the banking sector suffices to explain how banks foster credit bubbles. We first built a simple model of duopoly competition among banks to show how a rational bank would herd to follow the biased one. Then we compared the effects of optimism during upswings and pessimism in recessions. Finally, we offered a dynamization of the model to show how the credit cycle is amplified, as well as when and in which market niches over and underestimation effects are expected to be more pervasive. Five additional results were obtained:

15. Overconfident banks always follow their priors and lead the industry, while rational banks herd under some conditions we derive: there is a threshold bias such that when the biased bank is not too biased, the rational bank herds to grant credit as if it had biased expectations.

16. We showed that a credit boom of loans of low quality at a lower-than-rational rate is generated in all possible equilibrium market configurations that may emerge. Any of such booms are welfare increasing for low-quality borrowers.

17. A stronger result is that there would be no incentives for rational banks to correct the misallocations of their biased competitors. Hence, limits of arbitrage suggest bank-based systems are less likely to be informationally efficient than market based ones.

18. We found pessimism is not a powerful driver of credit cycles. When rational and boundedly rational banks compete, pessimism might only partially explain the *credit crunch*, as unbiased banks are not predicted to herd in any case. Thus, the model predicts financial crises are seeded during upturns, while the credit rationing observed during recessions would be a consequence of past excesses.

19. Finally, the effects are more pervasive the lower the quality of the niche market, since it is overoptimism what drives the boom and, for optimistic markets, the lower the probability of loan repayment the higher the required bias for an unbiased bank not to herd.

CONCLUSIONS OF THE THESIS AND FUTURE INVESTIGATION

The purpose of this doctoral thesis was to broaden the alternatives available to analyze the efficiency of banking systems when granting credit to the economy. In particular, we suggested how the way behavioral finance tests market efficiency in the context of financial markets could be applied to analyze the efficiency of bank-based systems as well. For such purpose, Part I and Part II provided an extensive literature review in order to lay the foundations for a better understanding of the main contributions of this thesis, which were presented in Part III.

In Part I we reviewed the main theories that study the efficiency of the financial system generally speaking, and of the banking industry in particular. These are the theories of credit and banking efficiency, the efficient market hypothesis (EMH), and behavioral finance. Thus, we firstly defined retail credit markets and reviewed the main theories of credit and banking efficiency. Then, we described the theoretical foundations of the EMH in financial markets and how behavioral finance challenges them. The review of the behavioral literature continued in Part II, where we firstly reviewed the myriad of biases and anomalies that dispute the efficiency postulates of standard finance, with a focus on two particular areas: prospect theory and overconfidence.

Then, Part III provided a rationale for behavioral finance to contradict the informational efficiency of bank-based systems as well. The analysis came in three instances. Firstly, we suggested a stepwise approach (Shleifer, 2000) would be a valid alternative to test the informational efficiency in retail credit markets, while it sidesteps the analysis of the allocative and operational efficiencies —often affected in bank-based systems by imperfect competition and informational asymmetries. Then, we contributed with an experimental research to deal with the first step in the stepwise approach. The results suggested that aggressive behavioral profiles, in terms of overconfidence and risk seeking (prospect theory), tend to be correlated to riskier credit strategies, in terms of providing credit to low-quality customers at a lower price. Finally, we offered a theoretical model to analyze the second and third steps in the stepwise approach: how would a duopoly of a rational and an overconfident bank would compete to grant credit to the economy, whether herding strategies would appear, and whether there are limits of arbitrage in the industry. The model contributes to explain how the credit cycle is amplified due to banking competition when some participants are affected by behavioral biases, and predicts it is an excessive optimism during upswings —rather than pessimism during crisis— what drives the cycle.

All together, the research provided in this doctoral thesis could be a relevant contribution to identify possible weaknesses of bank-based financial systems, and hence to promote complementary regulation —particularly on macroprudential regulation and the role of central banking. In particular, our model shows how behavioral biases might guide retail credit markets and why limits of arbitrage would imply bank-based systems are less likely to be informationally efficient than market-based ones.

Much academic research in recent years has focused on issues like how to avoid a correlated behavior by banks, managing systemic risk, which role central banks should play in promoting financial stability, etc. Macroprudential regulation tries to address the main drawback of traditional approach to banking regulation: capital requirements implicitly assume we can make a banking system safe by making individual banks safer, but evidence has shown this is false.[270] Regulation had assumed crashes occur randomly, but in reality crashes follow booms, which occur quite often because market discipline does not operate during upswings: risk falls in the up-phase of economic cycle, so banks expand their balance sheets, lower the cost of funding by using short term financing, and increase leverage (Brunnermeier et al., 2009). Macro-prudential regulation addresses the stability of the financial system as a whole. Among other measures, it requires countercyclical and contingent capital requirements, supervision of direct and indirect exposures and linkages, cross border (by IMF, FSB and BIS organizations) as well as domestic, higher capital buffers for systemically relevant financial institutions (SIFIs), and coordination across countries (Eichengreen et al., 2011). For instance Basel III, the set of regulatory standards for the banking industry, beyond requiring higher bank capital requirements and other actions, introduces a series of measures to reduce procyclicality, like promoting countercyclical capital buffers in good times that can be drawn upon in periods of stress.[271]

Another debate today is about the role private banks and central banking should have. Regarding banking crises, Beck (2011) concludes it is all about incentives: *"regulations should be shaped in a way that forces financial institutions to internalize all repercussions of their risk, especially the external costs of their potential failure"* (p. 2), particularly because bank-lending linkages appear to be the main driver of the transmission of stress (Balakrishnan et al., 2009). The debate about central banking, on the other hand, is around whether financial stability should be an explicit mandate of central banks. Many authors agree with that view —as well as with international coordination among central banks— but only as long as we are aware that monetary policy is not the best tool with which to address a bubble because asset price bubbles will not respond to small changes in interest rates (Eichengreen et al., 2011).

---

270 According to Brunnermeier et al. (2009), risk is endogenous to bank behavior, particularly because if many banks sell an asset when its risk increases (fire sales), the asset price will collapse. Some 'avenues' might have intensified such endogeneity: mark-to-market valuation, market-based measures of risk (like CDS spreads), an increased use of credit ratings —which tend to be correlated with market prices—, etc.

271 Some authors warn on the perils of *"a multiple, but uncoordinated, reform frameworks, such as the Basel III requirements, the Capital Requirements Directive IV in Europe, the Dodd–Frank Act in the US, and the Independent Commission on Banking Report in the UK"* (Beck, 2011, p. viii).

Would the behavioral approach introduced in this doctoral thesis provide further evidence on the pervasiveness of behavioral biases in the banking industry, then banking regulation should account for it. However, as Brunnermeier et al. (2009) say, *"solution is not more regulation per se, but better and different regulation. The solution must be regulate to internalize externalities (systemic risks)"* (p. xv). The behavioral approach we use in this thesis would come in support of countercyclical regulation; how to implement it, however, is beyond the scope of this thesis. Some biases might be corrected through internal debiasing procedures (incentives, career opportunities, firewalls, etc.); others, however, such as herding, would require authorities to intervene. Examples include allowing authorities to monitor bank's scorings to statistically ensure banks are not incurring in excessive risk-taking or predatory lending,[272] or other alternatives authorities may use to arbitrate credit markets.

Finally, whether it is desirable or not to impose limits to credit during booms and implement directed credit during recessions would only be an additional line of debate. Indeed, one should also consider the possibility that neither authorities would be efficient when 'hedging' credit markets: central banks and regulators must infer the 'fundamental level' of credit an economy requires given information available at the market (a sort-of-definition for EMH in retail credit markets) and apply the necessary policies. However, as well as private banks, they might also fail.

Future research

Some open lines of research were already mentioned. Chapter 6, for instance, provided a research agenda that suggested several means to test our behavioral approach. Firstly, through the empirical analysis of whether behavioral biases such as availability, representativeness, overconfidence, excessive optimism, risk seeking, and biased self-attribution, among others, might affect the decisions of CEOs and employees within the industry. Secondly, through the empirical observation of a credit market sentiment that would support the interpretation that the procyclicality of credit may have a behavioral explanation. This might be traced by either identifying the effects of a social contagion among market participants, or the empirical observation of a correlated credit market —manifested itself as episodes of overreaction, momentum, herding and/or excessive volume of credit.

In regards to the psychological tests in Chapter 7, several enhancements were suggested as well. First, in order to solve the problem detected in the test for overprecision, future tests will require having more questions per domain, while it would also be desirable to ask additional questions on personal experience to balance domains. In addition, other possibilities would include to introduce questions on abilities and perceptual tasks (Stankov et al., 2012) in the trivia test to moderate the general drift towards overestimation, and setting the computer application in the prospect theory test to refine answers that might be interpreted as a response error by asking an additional questions. Finally, two

[272] This is actually a suggestion by Professor Stiglitz, following our conversation in a private meeting in November 2011, available at http://www.dpeon.com/index.php/english/8-prof-stiglitz-in-a-coruna.html.

open questions in the test for prospect theory are how to improve loss aversion estimations, since sensibility of the value function to lower amounts of money varies across individuals, and how to foster more realistic answers, particularly in the negative domain.

The business simulation game introduced in Chapter 8 represents a first effort to explore the potential effects of behavioral biases over credit policies. However, time constraints to implement the series of psychological tests and the simulation game by the same set of participants imposed two important restrictions. The first restriction refers to the fact that the psychological tests implemented were required to be shorter versions of classic tests in the literature. Though, as argued in Chapter 7, the results obtained were broadly satisfactory, some limits were observed. In addition, the external validity of the results obtained critically depends on the accuracy of the test results at the individual level. In consequence, it would be desirable to perform repeated versions of the experiment with more time for participants to perform the tests. This would allow the introduction of more complete versions of the psychological tests, in order to determine whether the results in this thesis are replicable. The second restriction was the requirement that only one repetition of the business simulation game was to be performed. Again, the external validity of the results might be improved in future research if several rounds of the game with randomized economic scenarios are implemented. This would help mitigate the effects of a strategic behavior and avoid any randomization bias (Viera and Bangdiwala, 2007), as well as introducing the possibility to test the debiasing effects of learning and experience.

Finally, the model in Chapter 9 has its limits as well. First, the model is a simple one to describe how banks would compete and the effects behavioral biases among the industry might induce. Further extensions should consider the effects of informational asymmetries and adverse selection, alternative models of banking competition, the effects of bankruptcy costs, etc. Finally, another limitation of the model relies on the fact that it does not offer an endogenous explanation of the economic cycle. Rather than that, we take an exogenous (empirically observed) economic cycle to determine what the effects of over and underconfidence would be. Further extensions might introduce complementary explanatory variables for the optimism of the banking sector (e.g. collaterals, total amount of debt, past bankruptcies) besides the overall economic development and their rival agents' behavior to endogenize the cyclical behavior of the economy with this setup.

In addition, an open area of research would be to implement an experimental test of the theoretical model in Chapter 9 through a modified version of the business simulation game in Chapter 8. These ideas are yet to be worked out, but it would require to perform a competition among several participants granting credit to a pool of potential borrowers, in order to test whether the theoretical results obtained in Chapter 9 hold.

BIBLIOGRAPHIC REFERENCES

Abdellaoui, M. (2000), Parameter-free elicitation of utility and probability weighting functions, *Management Science* 46(11), 1497-1512.

Abdellaoui, M., C. Barrios and P.P Wakker (2007b), Reconciling introspective utility with revealed preference: Experimental arguments based on prospect theory, *Journal of Econometrics* 138, 356-378.

Abdellaoui, M., F. Vossmann and M. Weber (2005), Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty, *Management Science* 51, 1384-1399.

Abdellaoui, M., H. Bleichrodt and C. Paraschiv (2007a), Loss aversion under prospect theory: A parameter-free measurement, *Management Science* 53(10), 1659-1674.

Abdellaoui, M., H. Bleichrodt and O. L'Haridon (2008), A tractable method to measure utility and loss aversion under prospect theory, *Journal of Risk and Uncertainty* 36, 245-266.

Abel, A., G. Mankiw, L. Summers, and R. Zeckhauser (1989), Assessing dynamic efficiency: Theory and evidence, *Review of Economic Studies* 56, 1-19.

Aboody, D. and L. Baruch (2000), Information asymmetry, R&D, and insider gains, *Journal of Finance* 55(6), 2747-66.

Abreu, D. and M.K. Brunnermeier (2003), Bubbles and crashes, *Econometrica* 71, 173-204.

Acharya, V. and H. Naqvi (2012), The seeds of a crisis: A theory of bank liquidity and risk taking over the business cycle, *Journal of Financial Economics* 106, 349-366.

Ackert, L.F., B.K. Church, J. Tompkins and P. Zhang (2005), What's in a name? An experimental examination of investment behavior, *Review of Finance* 9, 281-304.

Affleck-Graves, J. and R.R. Mendenhall (1992), The relation between the Value Line enigma and post-earnings-announcement drift, *Journal of Financial Economics* 31, 75-96.

Aghion, P. and P. Bolton (1992), An incomplete contracts approach to corporate bankruptcy, *Review of Economic Studies* 59, 473-494.

Aigner, D., C.A.K. Lovell and P. Schmidt (1977), Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics* 6, 21-37.

Akerlof, G.A. (1970), The market for 'lemons': Quality uncertainty and the market mechanism, *Quarterly Journal of Economics* 84(3), 488–500.

Akerlof, G.A. (1979), The case against conservative macroeconomics: An inaugural lecture, *Economica* 46, 219-237.

Akerlof, G.A. and J.L. Yellen (1990), The fair wage-effort hypothesis and unemployment, *Quarterly Journal of Economics* 105(2), 255-283.

Akerlof, G.A. and R.J. Shiller (2009a), *Animal Spirits: How Human Psychology Drives the Economy, and Why It Matters for Global Capitalism*, Princeton University Press.

Akerlof, G.A. and R.J. Shiller (2009b), How animal spirits destabilize economies, *McKinsey Quarterly* 3, 127-135.

Akerman, G. (1957), The Cobweb theorem: A reconsideration, *Quarterly Journal of Economics* 71, 151-160.

Aktas, N., E. de Bodt and H. Van Oppens (2008), Legal insider trading and market efficiency, *Journal of Banking and Finance* 32(7), 1379-92.

Aktas, N., E. de Bodt, F. Declerck and H. Van Oppens (2007), The PIN anomaly around M&A announcements, *Journal of Financial Markets* 10(2), 169-191.

Alexander, S.S. (1961), Price movements in speculative markets: Trends or random walks, *Industrial Management Review* 2(2), 7-26.

Alicke, M.D. and O. Govorun (2005), The better-than-average effect, In M.D. Alicke, D. Dunning and J. Krueger (eds.) *The self in social judgment* (pp. 85-106), New York, Psychology Press.

Alicke, M.D., M.L. Klotz, D.L. Breitenvecher, T.J. Yurak and D.S. Vredenburg (1995), Personal contact, individuation, and the better-than-average effect, *Journal of Personality and Social Psychology* 68, 804-825.

Allais, M. (1953), Le comportement de l'homme rationnel devant le risque, critique des postulats et axiomes de l'Ecole Americaine, *Econometrica* 21, 503-546.

Allen, B. (1981), Generic existence of completely revealing equilibria for economies with uncertainty when prices convey information, *Econometrica* 49, 1173-1199.

Allen, B. (1982), Strict rational expectations equilibria with diffuseness, *Journal of Economic Theory* 27, 20-46.

Allen, F. and D. Gale (2000), Bubbles and crises, *The Economic Journal* 110(460), 236-255.

Allen, F., M.K.F. Chui and A. Maddaloni (2004), Financial systems in Europe, the USA and Asia, *Oxford Review of Economic Policy* 20(4), 490-508.

Allen, F., S. Morris and H.S. Shin (2006), Beauty contest and iterated expectations in asset markets, *Review of Financial Studies* 19(3), 719-752.

Alpert, M. and H. Raifa (1969), A progress report on the training of probability assessors, *Mimeo*, Reprinted in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Alti, A. and J. Sullaeman (2012), When do high stock returns trigger equity issues? *Journal of Financial Economics* 103, 61-87.

Altman, E.I. (1968), Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23(4), 589-609.

Amato J.D. and H.S. Shin (2003), Public and private information in monetary policy models, *BIS Working Papers No 138.*

Amihud, Y. (2002), Illiquidity ad stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5(1), 31-56.

Andersen, P. and N.C. Petersen (1993), A procedure for ranking efficiency units in data envelopment analysis, *Management Science* 39, 1261-64.

Andersen, T.G., T. Bollerslev, F.X. Diebold and P. Labys (2003), Modeling and forecasting realized volatility, *Econometrica* 71(2), 579-625.

Anderson, A. (2012), Trading and underdiversification, *Working Paper*, Institute for Financial Research.

Anderson, E.W., E. Ghysels and J.L. Juergens (2005), Do heterogeneous beliefs matter for asset pricing, *Review of Financial Studies* 18(3), 875-924.

Andreou, P.C., J.A. Doukas and C. Louca (2012), Corporate diversification and managerial overconfidence, *19th Annual Conference of the Multinational Finance Society*, Krakow, June 2012.

Ang, A. and G. Bekaert (2007), Stock return predictability: Is it there? *Review of Financial Studies* 20(3), 651-707.

Ang, A., J. Chen and Y. Xing (2001), Downside risk and the momentum effect, *NBER working paper* No. w8643.

Antelo, M. and D. Peón (2012), *Financial Markets: A Guided Tour*, New York: Nova Science Publishers.

Arbel, A. and P. Strebel (1982), The neglected and small firm effects, *Financial Review* 17(4), 201-218.

Arbel, A., S. Carvell and P. Strebel (1983), Giraffes, institutions and neglected firms, *Financial Analysts Journal* 39(3), 57-63.

Arditti, F. (1967), Risk and the required return on equity, *Journal of Finance* 22, 19-36.

Argenti, J. (1976), *Corporate Collapse: The causes and symptoms*, McGraw-Hill.

Argenti, J. (1984), Predicting corporate failure, *Institute of Chartered Accountants in England and Wales*, London.

Argyle, M. (1991), *Cooperation: The basis of sociability*, Routledge.

Arkes, H.R., D. Hirshleifer, D. Jiang and S.S. Lim (2008), Reference point adaptation: Tests in the domain of security trading, *Organizational Behavior and Human Decision Processes* 105, 67–81.

Arkes, H.R., D. Hirshleifer, D. Jiang and S.S. Lim (2010), A cross-cultural study of reference point adaptation: Evidence from China, Korea and the US, *Organizational Behavior and Human Decision Processes* 112(2), 99-111.

Aronson, E., T.D. Wilson and R.M. Akert (2006), *Social Psychology*, Pearson-Prentice Hall, sixth edit.

Arrow, K.J. (1964), The role of securities in the optimal allocations if risk bearing, *Review of Economic Studies* 31, 91-96.

Arrow, K.J. (1971), *Essays in the theory of risk bearing*, North Holland, Amsterdam.

Arrow, K.J. (1974), Limited information and economic analysis, *American Economic Review* 64, 1-10.

Arrow, K.J. and G. Debreu (1954), Existence of an equilibrium for a competitive economy, *Econometrica* 22(3), 265–290.

Arthurs, J.D., R.E. Hoskisson, L.W. Busenitz and R.A. Johnson (2008), Managerial agents watching other agents: Multiple agency conflicts regarding underpricing in IPO firms, *Academy of Management Journal* 51(2), 277-294.

Asch, S.E. (1952), *Social Psychology*, Prentice Hall.

Asquith, P. and D.W. Mullins (1986), Equity issues and offering dilution, *Journal of Financial Economics* 15, 61-89.

Asquith, P., P. Healy and K. Palepu (1989), Earnings and stock splits, *Accounting Review* 64, 387-403.

Asquith, P., R. Bruner and J.D. Mullins (1983), The gains to bidding firms from merger, *Journal of Financial Economics* 11, 121–139.

Atiase, R.K. (1985), Predisclosure information, firm capitalization, and security price behavior around earnings announcements, *Journal of Accounting Research* 23(1), 21-36.

Atiase, R.K. (1987), Market implications of predisclosure information: Size and exchange effects, *Journal of Accounting Research* 25(1), 168-176.

Aumann, R.J. (1976), Agreeing to disagree, *Annals of Statistics* 4 (6), 1236-39.

Ayton, P. and A.G.R. McClelland (1997), How real is overconfidence? *Journal of Behavioral Decision Making* 10(3), 279-285.

Azariadis, C. and B. Smith (1998), Financial intermediation and regime switching in business cycles, *The American Economic Review* 88(3), 516-536.

Bacchetta, P. and E. van Wincoop (2008), Higher order expectations in asset pricing, *Journal of Money, Credit and Banking* 40 (5), 837-866.

Bachelier, L. (1900), Théorie de la speculation, *Annales Scientifiques de l'École Normale Supérieure* 3 (17), 21–86.

Bagehot, W. (1872), *Lombard Street: A Description of the Money Market*, Reprint, 1999, John Wiley & Sons.

Bain, J.S. (1951), Relation of profit rate to industry concentration, *Quarterly Journal of Economics* 65, 293-324.

Baker, M. and J. Wurgler (2002), Market timing and capital structure, *Journal of Finance* 57(1), 1–32.

Baker, M. and J. Wurgler (2004), A catering theory of dividends, *Journal of Finance* 59(3), 1125-65.

Baker, M. and J. Wurgler (2007), Investor sentiment in the stock market, *Journal of Economic Perspectives* 21(2), 129-151.

Baker, M.P. and J.C. Stein (2004), Market liquidity as a sentiment indicator, *Journal of Financial Markets* 7(3), 271-299.

Baker, M.P., R. Ruback, and J. Wurgler (2007), Behavioral corporate finance: A survey, In E. Eckbo (ed.), *The Handbook of Corporate Finance: Empirical Corporate Finance*, New York, Elsevier/North Holland.

Balakrishnan, R., S. Danninger, S. Elekdag and I. Tytell (2009), How financial stress spreads: A first comprehensive look at the current crisis, *VoxEu.org*, available at www.voxeu.org/index.php?q=node/3500

Balasubramanian, S.K., I. Mathur and R. Thakur (2005), The impact of high-quality firm achievements on shareholder value: Focus on Malcolm Baldrige and J.D. Power and Associates Awards, *Journal of the Academy of Marketing Science* 33(4), 413-422.

Balcaen, S. and H. Ooghe (2006), 35 years of studies on business failure: An overview of the classical statistical methodologies and their related problems, *The British Accounting Review* 38, 63-93.

Baldwin, J.R. (1995), *The Dynamics of Industrial Competition*, Cambridge: Cambridge University Press.

Baley, W., A. Kumar and D. Ng (2011), Behavioral biases of mutual fund investors, *Journal of Financial Economics* 102, 1-27.

Bali, R. (2003), An empirical analysis of stock returns around dividend changes, *Applied Economics* 35(1), 51-61.

Ball, R. (1978), Anomalies in relationships between securities' yields and yield-surrogates, Journal of Financial Economics, 6 (2-3), 103-126.

Ball, R. (1992), The earning-price anomaly, *Journal of Accounting and Economics* 15, 319-345.

Ball, R. and E. Bartov (1996), How naïve is the stock market's use of earnings information, *Journal of Accounting and Economics* 21(3), 319-337.

Ball, R. and P. Brown (1968), An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Ball, R. and S.P. Kothari (1989), Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, *Journal of Financial Economics* 25, 51-74.

Ball, R., S.P. Kothari and J. Shanken (1995), Problems in measuring portfolio performance: An application to contrarian investment strategies, *Journal of Financial Economics* 38, 79-107.

Banerjee, A. V. (1992), A simple model of herd behavior, *The Quarterly Journal of Economics* 107(3), 797-817.

Bange, M.M. and T.W. Miller (2004), Return momentum and global portfolio allocations, *Journal of Empirical Finance* 11(4), 429-459.

Banker, R.D., A. Charnes and W.W. Cooper (1984), Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science* 39, 1261-64.

Banz, R.W. (1981), The relationship between return and market value of common stocks, *Journal of Financial Economics* 9(1), 3-18.

Barber, B.M. and T. Odean (2001), Boys will be boys: Gender, overconfidence, and common stock investment, *The Quarterly Journal of Economics* 116(1), 261-292.

Barber, B.M. and T. Odean (2002), Online investors: Do the slow die first? *Review of Financial Studies* 15, 455–89.

Barber, B.M. and T. Odean (2008), All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21(2), 785-818.

Barber, B.M., P.A. Griffin and B. Lev (1993), The fraud-on-the-market theory and the determinants of common stocks' efficiency, *Journal of Corporation Law* 19, 285-312.

Barberis, N. and A. Shleifer (2003), Style investing, *Journal of Financial Economics* 68, 161-199.

Barberis, N. and M. Huang (2001), Mental accounting, loss aversion and individual stock returns, *The Journal of Finance* 56(4), 1247-92.

Barberis, N. and M. Huang (2007), The loss aversion/narrow framing approach to the equity premium puzzle, In R. Mehra (ed.) *Handbook of Investments: Equity Premium*, North-Holland, Amsterdam, pp. 199–229.

Barberis, N. and M. Huang (2008), Stock as lotteries: The implication of probability weighting for security prices, *American Economic Review* 98(5), 2066–2100.

Barberis, N. and M. Huang (2009), Preferences with frames: A new utility specification that allows for the framing of risks, *Journal of Economics Dynamics & Control* 33(8), 1555-76.

Barberis, N. and R.H. Thaler (2003), A survey of Behavioral Finance, In G.M. Constantinides, M. Harris and R.M. Stulz (eds.), *Handbook of the Economics of Finance* 1(1), 1053-1128.

Barberis, N. and W. Xiong (2009), What drives the disposition effect? An analysis of a long-standing preference-based explanation, *The Journal of Finance* 64(2), 751-784.

Barberis, N., A. Shleifer and R. Vishny (1998), A model of investor sentiment, *Journal of Financial Economics* 49(3), 307-343.

Barberis, N., M. Huang and R.H. Thaler (2006), Individual preferences, monetary gambles, and stock market participation: A case for narrow framing, *American Economic Review* 96, 1069–1090.

Barberis, N., M. Huang and T. Santos (2001), Prospect theory and asset prices, *The Quarterly Journal of Economics* 116(1), 1-53.

Bar-Hillel, M. (1973), On the subjective probability of compound events, *Organizational Behavior & Human Performance* 9, 396-406.

Bar-Hillel, M. (1982), Studies of representativeness, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Barro, R.J. (1976), Rational expectations and the role of monetary policy, *Journal of Monetary Economics* 2, 241-254.

Barros, C.P. and P. García-del-Barrio (2010), Productivity drivers and market dynamics in the Spanish first division football league, *Journal of Productivity Analysis* 35, 5-13.

Barry, C.B. and S.J. Brown (1984), Differential information and the small firm effect, *Journal of Financial Economics* 13(2), 283-294.

Barry, C.B., E. Goldreyer, L. Lockwood and M. Rodriguez (2002), Robustness of size and value effects in emerging equity markets, 1985-2000, *Emerging Markets Review* 3(1), 1-30.

Barsky, R. and J.B. DeLong (1993), Why does the stock market fluctuate? *Quarterly Journal of Economics* 108, 291-311.

Bartov, E., S. Radhakrishnan and I. Krinsky (2000), Investor sophistication and patterns in stock returns after earnings announcements, *Accounting Review* 75(1), 43-63.

Basu, S. (1977), Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient markets hypothesis, *Journal of Finance* 32, 663-682.

Basu, S. (1983), The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* 12, 129-156.

Basu, S. (1997), The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics* 24(1), 3-37.

Baucells, M., M. Weber and F. Welfens (2011), Reference point formation and updating: Theory and experiments, *Journal Management Science* 57(3), 506-519.

Bean, Ch. (2010), The great moderation, the great panic and the great contraction, *Journal of the European Economic Association* 8, 289-325.

Beard, C.G. and R.W. Sias (1997), Is there a neglected-firm effect? *Financial Analysts Journal* 53(5), 19-23.

Beaver, W. (1966), Market prices, financial ratios and the prediction failure, *Journal of Accounting Research* 6, 179-192.

Beck, T. (ed.) (2011), The future of banking, *VoxEU.org eBook, CEPR*. Available at http://www.voxeu.org/sites/default/files/file/the_future_of_banking.pdf

Beeby, M., S.G. Hall and S.B. Henry (2001), Rational expectations and near rational alternatives: how best to form expectations, *ECB working paper*, European Central Bank.

Bekaert, G. and C.R. Harvey (1997), Emerging equity market volatility, *Journal of Financial Economics* 43, 29-77.

Bekaert, G., M. Wei and Y. Xing (2007), Uncovered interest parity and the term structure, *Journal of International Money and Finance* 26, 1038-69.

Bell, D.E. (1982), Regret in decision making under uncertainty, *Operations Research* 30(5), 961-981.

Bell, D.E. (1985), Disappointment in decision making under uncertainty, *Operations Research* 33(1), 1-27.

Bell, D.E. and P.C. Fishburn (2000), Utility functions for wealth, *Journal of Risk and Uncertainty* 20, 5-44.

Belsky, G. and T. Gilovich (1999), *Why smart people make big money mistakes and how to correct them: Lessons from the new science of behavioral economics*, Simon & Schuster.

Bem, D.J. (1965), An experimental analysis of self-persuasion, *Journal of Experimental Social Psychology* 1, 199-218.

Bem, D.J. (1967), Self-perception: An alternative interpretation of cognitive dissonance phenomena, *Psychological Review* 74(3), 183-200.

Benartzi, S. (2001), Excessive extrapolation and the allocation of 401(k) accounts to company stock? *American Economic Review* 91(1), 79-98.

Benartzi, S. and R.H. Thaler (1995), Myopic loss aversion and the equity premium puzzle, *The Quarterly Journal of Economics* 110(1), 73-92.

Benartzi, S. and R.H. Thaler (2001), Naïve diversification strategies in defined contribution savings plans, *American Economic Review* 91, 79-98.

Benartzi, S. and R.H. Thaler (2007), Heuristics and biases in retirement savings behavior, *Journal of Economic Perspectives* 21(3), 81-104.

Beneish, M.D. and M.E. Vargus (2002), Insider trading, earnings quality and accrual mispricing, *Accounting Review* 77(4), 755-791.

Benes, J. and M. Kumhof (2012), The Chicago Plan revisited, *IMF Working Paper 12/202*, IMF, August 2012.

Benoit, J-P. and J. Dubra (2011), Apparent overconfidence, *Econometrica* 79(5), 1591-1625

Benston, G. and C.W. Smith (1976), A transaction cost approach to the theory of financial intermediation, *Journal of Finance* 31, 215-231.

Berg, S.A., F.R. Forsund and E.S. James (1992), Malmquist indices of productivity growth during the deregulation of Norwegian banking, 1980-89. *Scandinavian Journal of Economics* 94, S211-S228.

Berger, A.N. (1993), Distribution-free estimates of efficiency in the U.S. banking industry and tests of the standard distributional assumptions, *Journal of Productivity Analysis* 4, 261-292.

Berger, A.N. (1995), The profit-structure relationship in banking: Tests of market-power and efficient-structure hypotheses, *Journal of Money, Credit and Banking* 27(2), 404-431.

Berger, A.N. and D.B. Humphrey (1991), The dominance of inefficiencies over scale and product mix economies in banking, *Journal of Monetary Economics* 28, 117-148.

Berger, A.N. and D.B. Humphrey (1997), Efficiency of financial institutions: International survey and directions for future research, *European Journal of Operational Research* 98, 175-212.

Berger, A.N. and L.J. Mester (1997), Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking and Finance* 21, 895-947.

Berger, A.N. and R. DeYoung (1997), Problem loans and cost efficiency in commercial banks, *Journal of Banking and Finance* 21, 849-870.

Berger, A.N. and T.H. Hannan (1997), Using efficiency measures to distinguish among alternative explanations of the structure-performance relationship in banking, *Managerial Finance* 23(1), 6-31.

Berk, J.B., R.C. Green and V. Naik (1999), Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553-1608.

Bernanke, B. (2010), Causes of the recent financial and economic crisis: Before the Financial Crisis Inquiry Commission, Available: www.federalreserve.gov/newsevents/testimony/bernanke20100902a.htm

Bernanke, B. and A.S. Blinder (1988), Credit, money and aggregate demand, *American Economic Review* 78(29), 435-439.

Bernard, V. (1992), Stock price reactions to earnings announcements, In R.H. Thaler (ed.), *Advances in Behavioral Finance*, Russell Sage Foundation.

Bernard, V. (1993), Stock price reaction to earnings announcement: A summary of recent anomalous evidence and possible explanations, In Thaler, R.H. (ed.), *Advances in Behavioral Finance*, Russel Sage Foundation, NY.

Bernard, V.L. and J.K. Thomas (1989), Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27, 1–48.

Bernard, V.L. and J.K. Thomas (1990), Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Bernhardt, D., M. Campello and E. Kutsoati (2006), Who herds? *Journal of Financial Economics* 80, 657-675.

Bernoulli, J. (1713), *Ars conjectandi, opus posthumum. Accedit Tractatus de seriebus infinitis, et epistola gallicé scripta de ludo pilae reticularis*, Basileae, impensis Thurnisiorum fratrum.

Berument, H. and H. Kiymaz (2001), The day of the week effect on stock market volatility, *Journal of Economics and Finance* 25(2), 181-193.

Bhandari, L.C. (1988), Debt/Equity ratio and expected common stock returns: empirical evidence, *Journal of Finance* 43, 507-528.

Biais, B. and P.L. Bossaerts (1998), Asset prices and trading volume in a beauty contest, *Review of Economic Studies* 65 (2), 307-340.

Biais, B., D. Hilton, K. Mazurier and S. Pouget (2005), Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market, *Review of Economic Studies* 287-312.

Biais, B., P. Bossaerts and C. Spatt (2010), Equilibrium asset pricing and portfolio choice under asymmetric information, *Review of Financial Studies* 23(4), 1503-43.

Bijleveld, E., R. Custers and H. Aarts (2012) Human reward pursuit: From rudimentary to higher-level functions, *Current Directions in Psychological Science* 21(3), 194-199.

Bikhchandani, S., D. Hirshleifer and I. Welch (1998), Learning from the behavior of others: Conformity, fads, and informational cascades, *The Journal of Economic Perspectives* 12(3), 151-170.

Bilson, C., A. Frino and R. Heaney (2005), Australian retail fund performance persistence, *Accounting and Finance* 45(1), 25-42.

Birnbaum, M.H. (2008a), New paradoxes of risky decision making, *Psychological Review* 115(2), 463-501.

Birnbaum, M.H. (2008b), New tests of cumulative prospect theory and the priority heuristic: Probability outcome tradeoff with branch splitting, *Judgment and Decision Making* 3, 304-316.

Black F., M.C. Jensen, and M. Scholes (1972), The capital asset pricing model: Some empirical tests. In: M. Jensen (ed.), *Studies in the theory of capital markets*, Praeger.

Black, F. (1976), The dividend puzzle, *Journal of Portfolio Management* 2, 72-77.

Black, F. (1986), Noise, *Journal of Finance* 41(3), 529–543.

Black, F. and M. Scholes (1973), The Pricing of Options and Corporate Liabilities, *Journal of Political Economy* 81, 637-654.

Blake, D. (2000), *Financial Market Analysis*. Chichester: John Wiley & Sons, 2nd edition.

Bleichrodt, H. and J.L. Pinto (2000), A parameter-free elicitation of the probability weighting function in medical decision analysis, *Management Science* 46(11), 1485–96.

Bodie, Z. (1976), Common stocks as a hedge against inflation, *Journal of Finance* 31, 459-470.

Böge, W. and T. Eisele (1979), On solutions of Bayesian games, *International Journal of Game Theory* 8, 193-215.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics* 31(3), 307-327.

Bolton, G.E. and A. Ockenfels (2000), ERC: A theory of equity, reciprocity, and competition, *American Economic Review* 90(1), 166-193.

Bomfim, A.N. (2003), Pre-announcement effects, news effects, and volatility: Monetary policy and the stock market, *Journal of Banking and Finance* 27(1), 133-151.

Bonin, J.P., I. Hasan and P. Wachtel (2005), Bank performance, efficiency and ownership in transition countries, *Journal of Banking and Finance* 29, 31-53.

Booij, A.S., B.M.S. van Praag and G. van de Kuilen (2010), A parametric analysis of prospect's theory functionals for the general population, *Theory and Decision* 68, 115-148.

Borio, C.E.V. and I. Shim (2007), What can (macro-) prudential policy do to support monetary policy? *Bank of International Settlements*, BIS Working Papers 242, Available: http://www.bis.org/publ/work242.htm

Bossaerts, P.L. (1995), Speculative behavior and the functioning of financial markets: discussion, *Moneda y Crédito* 200, 39-44.

Bouchaud, J-P, J.D. Farmer and F. Lillo (2008), How markets slowly digest changes in supply and demand, In T. Hens and K. Schenk-Hoppe (eds.) *Handbook of Financial Markets: Dynamics and Evolution*, 57-156. Elsevier.

Bowman, D., M. Minehart and M. Rabin (1999), Loss aversion in a consumption-savings model, *Journal of Economic Behavior and Organization* 38, 155-178.

Boz, E. and E.G. Mendoza (2014), Financial innovation, the discovery of risk, and the U.S. credit crisis, *Journal of Monetary Economics* 62, 1-22.

Brandstätter, E., G. Gigerenzer and R. Hertwig (2006), The priority heuristic: Making choices without trade-offs, *Psychological Review* 113(2), 409–432.

Brav, A. and P.A. Gompers (1997), Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies, *Journal of Finance* 52(5), 1791-1821.

Brav, A., J.R. Graham, C.R. Harvey and R. Michaely (2005), Payout policy in the 21st century, *Journal of Financial Economics* 77, 483-527.

Bray, M.M. and N.E. Savin (1986), Rational expectations equilibrium, learning and model specification, *Econometrica* 54 (5), 1129-1160.

Breeden, D.T. (1979), An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7 (2), 265-96.

Brennan, M. (1991), A perspective on accounting and stock prices, *Accounting Review* 66(1), 67-79.

Brenner, L.A., D.J. Koehler, V. Liberman and A. Tversky (1996), Overconfidence in probability and frequency judgments: A critical examination, *Organizational Behavior and Human Decision Processes* 65(3), 212-219.

Briec, W. (1997), A graph type extension of Farrell technical efficiency measure, *Journal of Productivity Analysis* 8, 95-110.

Brock, W.A. and C.H. Hommes (1998), Heterogeneous beliefs and routes to chaos in a simple asset pricing model, *Journal of Economic dynamics and control* 22, 1235-1274.

Brown, C. (1997), Consumer credit and the propensity to consume: Evidence from 1930, *Journal of Post Keynesian Economics* 19(4), 617-638.

Brown, C. (2007), Financial engineering, consumer credit, and the stability of effective demand, *Journal of Post Keynesian Economics* 29(3), 427-453.

Brown, S.J., W. Goetzmann, R.G. Ibbotson and S.A. Ross (1992), Survivorship bias in performance studies, *The Review of Financial Studies* 5(4), 553-580.

Bruner, J.S. and M.C. Potter (1964), Interference in visual recognition, *Science*, 144(3617), 424-425.

Brunnermeier, M. and S. Nagel (2004), Hedge funds and the technology bubble, *Journal of Finance* 59(5), 2013-2040.

Brunnermeier, M., A. Crocket, C. Goodhart, A.D. Persaud and H. Shin (2009), The fundamental principles of financial regulation, *Centre for Economic Policy and Research*, Geneva Reports on the World Economy, 11, available at http://www.cepr.org/pubs/books/cepr/booklist.asp?cvno=P197

Brunswik, E. (1952), *The Conceptual Framework of Psychology*, Chicago: Chicago University Press.

Burnside, C., B. Han, D. Hirshleifer and T.Y. Wang (2011), Investor overconfidence and the forward premium puzzle, *Review of Economic Studies* 78, 523-558.

Burson, K.A., R.P. Larrick and J. Klayman (2006), Skilled or unskilled, but still unaware of it: How perceptions of difficulty drive miscalibration in relative comparisons, *Journal of Personality and Social Psychology* 90(1), 60-77.

Byun, J. and M.S. Rozeff (2003), Long-run performance after stock splits: 1927 to 1996, *Journal of Finance* 58(3), 1063-85.

Caballero, R. and A. Krishnamurthy (2006), Bubbles and capital flow volatility: Causes and risk management, *Journal of Monetary Economics* 53(1), 33-53.

Cagan, P. (1956), The monetary dynamics of hyperinflation, in Friedman, M. (ed.), *Studies in the quantity theory of money*, University of Chicago Press, Chicago, 25-120.

Calvo-Flores, A. and D. García Pérez (2002), Relación entre la posición económica y financiera de la empresa y los estados de fracaso empresarial, In F. Doldán and M. Rodríguez (eds.) *La Gestión del Riesgo de Crédito: Métodos y Modelos de Predición de la Insolvencia Empresarial*, AECA, 47-71.

Camerer, C.F. (2000), Prospect theory in the wild: Evidence from the field, In D. Kahneman and A. Tversky (eds.), *Choices, Values, and Frames*, Cambridge University Press, pp. 288-300.

Camerer, C.F. (2007), Neuroeconomics: Using neuroscience to make economic predictions, *The Economic Journal* 117, C26-C42.

Camerer, C.F. and D. Lovallo (1999), Overconfidence and excess entry: An experimental approach, *The American Economic Review* 89(1), 306-318.

Camerer, C.F. and G. Loewenstein (2004), Behavioral Economics: Past, present, future, In C.F. Camerer, G. Loewenstein and M. Rabin (eds.), *Advances in Behavioral Economics*, Princeton University Press, 3-51.

Camerer, C.F. and R.H. Thaler (1995), Anomalies: Ultimatums, dictators and manners, *Journal of Economic Perspectives* 9(2), 209-219.

Camerer, C.F. and R.M. Hogarth (1999), The effects of financial incentives in experiments: A review and capital-labor-production framework, *Journal of Risk and Uncertainty* 19, 7–42.

Camerer, C.F. and T-H. Ho (1994), Violations of the betweenness axiom and nonlinearity in probability, *Journal of Risk and Uncertainty* 8, 167-196.

Camerer, C.F., G. Loewenstein and D. Prelec (2004), Neuroeconomics: Why Economics needs brains, *Scandinavian Journal of Economics* 106(3), 555-579.

Camerer, C.F., G. Loewenstein and D. Prelec (2005), Neuroeconomics: How neuroscience can inform Economics, *Journal of Economic Literature* 43(1), 9-64.

Campbell, J.Y. (1987), Stock returns and the term structure, *Journal of Financial Economics* 18(2), 373-399.

Campbell, J.Y. (1991), A variance decomposition for stock returns, *Economic Journal* 101, 157-179.

Campbell, J.Y. (2000), Asset pricing at the millennium, *Journal of Finance* 55(4), 1515-68.

Campbell, J.Y. and A. Kyle (1993), Smart money, noise trading and stock price behavior, *Review of Economic Studies* 60, 1-34.

Campbell, J.Y. and M. Yogo (2006), Efficient tests of stock return predictability, *Journal of Financial Economics* 81(1), 27-60.

Campbell, J.Y. and R.J. Shiller (1987), Cointegration and tests of present value models, *Journal of Political Economy* 95, 1062-1088.

Campbell, J.Y. and R.J. Shiller (1988a), The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-227.

Campbell, J.Y. and R.J. Shiller (1988b), Stock prices, earnings, and expected dividends, *Journal of Finance* 43 (3), 661-676.

Campbell, J.Y. and R.J. Shiller (1991), Yield spreads and interest rate movements: A bird's eye view, *Review of Economic Studies* 58, 495-514.

Campbell, J.Y., A.W. Lo and A.C. MacKinlay (1996), *The econometrics of financial markets*, Princeton: Princeton University Press.

Cao, H.H., B. Han, D. Hirshleifer and H.H. Zhang (2011), Fear of the unknown: Familiarity and economic decisions, *Review of Finance* 15(19), 173-206.

Carling, K., T. Jacobson, J. Linde and K. Roszbach (2007), Corporate credit risk modelling and the macroeconomy, *Journal of Banking and Finance* 31(1), 845-868.

Carpenter, S.B. and S. Demiralp (2010), Money, reserves, and the transmission of monetary policy: Does the money multiplier exist? *Finance and Economics Discussion Series*, Washington: Federal Reserve Board.

Cason, T. and C. Noussair (2001), *Advances in Experimental Markets*, Springer, Studies in Economic Theory, 1st edition.

Caves, D.W., L.R. Christensen and W.E. Diewert (1982), The economic theory of index numbers and the measurement of input, output, and productivity, *Econometrica* 50(6), 1393-1414.

Cespa, G. and X. Vives (2009), Dynamic trading and asset prices: Keynes vs. Hayek, *CESifo Working Paper Series No. 2839*.

Chan, L.K.C. (1988), On the contrarian investment strategy, *Journal of Business* 61(2), 147-163.

Chan, L.K.C., N. Jegadeesh and J. Lakonishok (1996), Momentum strategies, *Journal of Finance* 51(5), 1681-1713.

Chan, L.K.C., Y. Hamao and J. Lakonishok (1991), Fundamentals and stock returns in Japan, *Journal of Finance* 46(5), 1739-1764.

Chapman, G.B. and E.J. Johnson (1994), The limits of anchoring, *Journal of Behavioral Decision Making* 7, 223-242.

Chapman, L.J. and J. Chapman (1971), Test results are what you think they are, *Psychology Today* 18-22, Reprinted in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Charest, G. (1978), Dividend information, stock returns and market efficiency-II, *Journal of Financial Economics* 6, 297-330.

Charnes, A. (1990), Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks, *Journal of Econometrics* 46(1-2), 73-91.

Charnes, A., W.W. Cooper and E. Rhodes (1978), Measuring the efficiency of decision-making units, *European Journal of Operational Research* 2, 429-444.

Charnes, A., W.W. Cooper, B. Golany, L.M. Seiford and J. Stutz (1985), Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical productions functions, *Journal of Econometrics* 30, 91-107.

Charnes, A., W.W. Cooper, L.M. Seiford and J. Stutz (1982), A multiplicative model of efficiency analysis, *Socio-Economic Planning Sciences* 16(5), 223-224.

Chateauneuf, A. and M. Cohen (1994), Risk seeking with diminishing marginal utility in a non-expected utility model, *Journal of Risk and Uncertainty* 9, 77-91.

Chen, G., K.A. Kim, J.R. Nofsinger and O.M. Rui (2007), Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors, *Journal of Behavioral Decision Making* 20(4), 425-451.

Chen, H. and V. Singal (2004), All things considered, taxes drive the January effect, *Journal of Financial Research* 27(3), 351-372.

Chen, H., R. Roll, and S.A. Ross (1986), Economic forces and the stock market, *Journal of Business* 56, 383-403.

Chen, H.-L. and W.F.M. De Bondt (2004), Style momentum within the S&P-500 Index, *Journal of Empirical Finance* 11(4), 483-507.

Chen, Q. and W. Jiang (2006), Analysts' weighting of private and public information, *Review of Financial Studies* 19, 319-355.

Cherchye, L., T. Kuosmanen and T. Post (2000), What is the economic meaning of FDH? A reply to Thrall, *Journal of Productivity Analysis* 13, 263-267.

Chopra, N., J. Lakonishok and J. Ritter (1992), Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics* 31, 235-268.

Chordia, T. and L. Shivakumar (2002), Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985-1019.

Chui, A.C.W., S. Titman and K.C.J. Wei (2010), Individualism and momentum around the world, *Journal of Finance* 65(1), 361-392.

Clement, M.B. and S.Y. Tse (2005), Financial analyst characteristics and herding behavior in forecasting, *Journal of Finance* 60, 307–41.

Coase, R.H. (1960), The problem of social cost, *Journal of Law and Economics* 3(1), 1–44.

Cochrane, J.H. (2002), Stocks as money: Convenience yield and the tech-stock bubble, *Working Paper No. 8987*, NBER.

Coelli, T.J., P. Rao and G.E. Battese (1998), *An introduction to efficiency and productivity analysis*, Kluwer, Boston.

Cohen, D.A. and P. Zarowin (2010), Accrual-based and real earnings management activities around seasoned equity offerings, *Journal of Accounting and Economics* 50(1), 2-19.

Cokely, E.T. and C.M. Kelley (2009), Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation, *Judgmental Decision Making* 4, 20–33.

Committee of European Banking Supervisors CEBS (2010), *2010 EU wide stress testing*, sited (28/07/2010) at www.c-ebs.org/EuWideStressTesting.aspx

Condie, S. and J. Ganguli (2011), Informational efficiency with ambiguous information, *Economic Theory* 48 (2), 229-242.

Conrad, J. and G. Kaul (1993), Long-term market overreaction or biases in computed returns? *Journal of Finance* 48, 39-64.

Conrad, J. and G. Kaul (1998), An anatomy of trading strategies, *Review of Financial Studies* 11, 489-519.

Conrad, J., B. Cornell, W.R. Landsman and B.R. Rountree (2006), How do analyst recommendations respond to major news, *Journal of Financial and Quantitative Analysis* 41(1), 25-49.

Cooper, M. (1999), Filter rules based on price and volume in individual security overreaction, *Review of Financial Studies* 12(4), 901-935.

Cootner, P.H. (1962), Stock prices: Random vs. systematic changes, *Industrial Management Review* 3 (2), 24-45.

Copeland, L.S. (1989), *Exchange rates and international finance*, Addison Wesley: Reading Mass, Workingham.

Copeland, T. and D. Mayers (1982), The Value Line enigma (1965-1978): A case study of performance evaluation issues, *Journal of Financial Economics* 10, 289-321.

Cosmides, L. and J. Tooby (1990), Is the mind a frequentist? *Second Annual Meeting of the Human Behavior and Evolution Society*, LA, CA. Cited in G. Gigerenzer (1991), How to make cognitive illusions disappear: Beyond 'heuristics and biases', In W. Stroebe and M. Hewstone (eds.), *European Review of Social Psychology*, Wiley.

Cosmides, L. and J. Tooby (1996), Are humans good intuitive statisticians after all? Rethinking some conclusions from the literature on judgment under uncertainty, *Cognition* 58(1), 1-73

Courtis, J.K. (1987), Modelling a financial ratios categoric framework, *Journal of Business, Finance and Accounting* 5(4), 371-386.

Cowen, A., B. Groysberg and P. Healy (2006), Which types of analyst firms are more optimistic? *Journal of Accounting and Economics*, 41(1-2), 119-146.

Crawford, J.D. and L. Stankov (1996), Age differences in the realism of confidence judgments: A calibration study using tests of fluid and crystallized intelligence, *Learning and Individual Differences* 8(2), 83-103.

Cross, F. (1973), The behavior of stock prices on Fridays and Mondays, *Financial Analysts Journal* 29, 67-69.

Crutzen, N. and D. Van Caillie (2008), The business failure process: An integrative model of the literature, *Review of Business and Economics* 53(3), 287-316.

Cuadras, X., A.S. Fernández and J.R. Rosés (2002), Productividad, competencia e innovación en la banca privada española, *Revista de Historia Económica* 3, 2002.

Curcio, R., C. Goodhart, D. Guillaume and R. Payne (1997), Do technical trading rules generate profits? Conclusions from the intra-day foreign exchange market, *International Journal of Finance and Economics* 2(4), 267-280.

Cutler, D., J.M. Poterba and L.H. Summers (1990), Speculative dynamics and the role of feedback traders, *American Economic Review Papers and Proceedings* 80, 63-68.

Cutler, D., J.M. Poterba and L.H. Summers (1991), Speculative dynamics, *Review of Economic Studies* 58, 529-46.

Daniel, K.D. and S. Titman (2006), Market reactions to tangible and intangible information, Journal of Finance 61, 1605–43.

Daniel, K.D., D. Hirshleifer and A. Subrahmanyam (1998), Investor psychology and security market under- and overreactions, *The Journal of Finance* 53(6), 1839-85.

Daniel, K.D., D. Hirshleifer and A. Subrahmanyam (2001), Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56(3), 921-965.

Daniel, K.D., D. Hirshleifer and S.H. Teoh (2002), Investor psychology in capital markets: Evidence and policy implications, *Journal of Monetary Economics* 49(1), 139-209

Daouia, A. and L. Simar (2007), Nonparametric efficiency analysis: a multivariate conditional quantile approach, *Journal of Econometrics* 140(2), 375-400.

Darley, J.M. and P.H. Gross (1983), A hypothesis-confirming bias in labeling effects, *Journal of Personality & Social Psychology* 44(1), 20-33.

Das, S., H. Markowitz, J. Scheid and M. Statman (2010), Portfolio optimization with mental accounts, *Journal of Financial and Quantitative Analysis* 45(2), 311-334.

Dawes, R.M. (1979), The robust beauty of improper linear models in decision making, *American Psychologist* 34, 571-582.

Dawes, R.M. and M. Mulford (1996), The false consensus effect and overconfidence: Flaws in judgment or flaws in how we study judgment? *Organizational Behavior and Human Decision Processes* 65(3), 201-211.

De Bondt, W.F.M. and F.P.C. Wolff (2004), Introduction to the special issue on Behavioral Finance, *Journal of Empirical Finance* 11, 423-427.

De Bondt, W.F.M. and R.H. Thaler (1985), Does the stock market overreact? *Journal of Finance* 40(3), 793-805.

De Bondt, W.F.M. and R.H. Thaler (1987), Further evidence on investor overreaction and stock market seasonality, *The Journal of Finance* 42(3), 557-581.

De Bondt, W.F.M. and R.H. Thaler (1995), Financial decision-making in markets and firms: A behavioral perspective, In R. Jarrow et al. (ed.), *Handbooks in Operations Research and Management Science* 9, Amsterdam: Elsevier: 385–410.

De Finetti, B. (1931), Sul significato soggetivo della probabilità. *Fundamenta Matematicae* 17, 298-329.

De Finetti, B. (1937). La prévision: Ses lois logiques, ses sources subjetives. *Ann. Inst. H. Poincaré* 7, 1-68.

De Freitas, S. and M. Oliver (2006), How can exploratory learning with games and simulations within the curriculum be most effectively evaluated? *Computers & Education* 46(3), 249-264.

De Haas, R. and N. van Horen (2011), Running for the exit: International banks and crisis transmission, *DNB Working Papers* 279, Netherlands Central Bank, Research Department.

Dean, W.G. and R. Faff (2011), Feedback trading and the behavioral ICAPM: Multivariate evidence across international equity and bond markets, *Applied Financial Economics* 21(22), 1665-78.

Debreu, G. (1959), *Theory of Value*, New York: Wiley.

Dechow, P., W. Ge and C. Schrand (2010), Understanding earnings quality: A review of the proxies, their determinants and their consequences, *Journal of Accounting and Economics* 50, 344-401.

Del Brío, E.B. (2003), Revisión de los contrastes empíricos de la forma fuerte de eficiencia, *Revista Europea de Dirección y Economía de la Empresa* 12(2), 31-56.

Dell'Acqua, A., L.L. Etro, E. Teti and P. Barbalace (2013), Market value and corporate debt: The 2006-2010 international evidence, *Applied Financial Economics* 23, 495-504.

DellaVigna, S. (2009), Psychology and Economics: Evidence from the field, *Journal of Economic Literature* 47(2), 315-372.

DellaVigna, S. and E. Kaplan (2007), The Fox News effect: Media bias and voting, *The Quarterly Journal of Economics* 122(3), 1187-1234.

DellaVigna, S. and J.M. Pollet (2009), Investor inattention and Friday earnings announcements, *Journal of Finance* 64(2), 709-749.

DellaVigna, S. and U. Malmendier (2006), Paying not to go to the gym, *The American Economic Review* 96(3), 694-719.

DeLong, J.B., A. Shleifer, L. Summers and R.J. Waldmann (1990a), Noise trader risk in financial markets, *Journal of Political Economy* 98, 703-738.

DeLong, J.B., A. Shleifer, L. Summers and R.J. Waldmann (1990b), Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

DeLong, J.B., A. Shleifer, L. Summers, and R.J. Waldmann (1991), The survival of noise traders in financial markets, *Journal of Business* 64, 1-20.

Dempsey, S.J. (1989), Predisclosure information search incentives, analyst following and earnings announcement price response, *Accounting Review* 64(4), 748-757.

Demsetz, H. (1973), Industry structure, market rivalry and public policy, *Journal of Law and Economics* 16(1), 1-9.

Demsetz, H. and K. Lehn (1985), The structure of corporate ownership: Causes and consequences, *Journal of Political Economy* 93(6), 1155-77.

Denis, D.J. and I. Osobov (2008), Why do firms pay dividends? International evidence on the determinants of dividend policy, *Journal of Financial Economics* 89, 62-82.

Dennis, D.K. and J.J. McConnell (1986), Corporate mergers and security returns, *Journal of Financial Economics* 16(2), 143-187.

Deprins, A., L. Simar and H. Tulkens (1984), Measuring labor efficiency in post offices, In M. Marchand, P. Pestieau and H. Tulkens (eds.), *The performance of public enterprises: concepts and measurement*, Elsevier, Amsterdam, chapter 10, 243-268.

Desai, H., S. Rajgopal and M. Venkatachalam (2004), Value-glamour and accruals mispricing: One anomaly or two? *Accounting Review* 79(2), 355-385.

Deshmukh, S., A.M. Goel and K.M. Howe (2010), CEO overconfidence and dividend policy, *SSRN eLibrary.*

Dharan, B. and D. Ikenberry (1995), The long-run negative drift of post-listing stock returns, *Journal of Finance* 50, 1547-1574.

Di Blasio, P. and L. Milani (2008), Computer-mediated communication and persuasion: Peripheral vs. central route to opinion shift, *Computers in Human Behavior* 24(3), 798-815.

Diamond, D.W. (1984), Financial intermediation and delegated monitoring, *Review of Economic Studies* 51(3), 393-414.

Diamond, D.W. (1991), Monitoring and reputation: The choice between bank loans and directly placed debt, *Journal of Political Economy* 99(4), 689-721.

Diamond, D.W. and P. Dybig (1983), Bank runs, deposit insurance and liquidity, *Journal of Political Economy* 91, 401-419.

Diether, K.B., C.J. Malloy and A. Scherbina (2002), Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-41.

Diether, K.B., K.-H. Lee and I.M. Werner (2009), Short-sale strategies and return predictability, *Review of Financial Studies* 22(2), 575-607.

Djankov, S., C. McLiesh and A. Shleifer (2005), Private credit in 129 countries, *NBER Working Paper Series* w11078, available at SSRN: http://ssrn.com/abstract=652366

Doidge, C., G.A. Karolyi and R.M. Stulz (2004), Why are foreign firms listed in the U.S. worth more? *Journal of Financial Economics* 71(2), 205-238.

Dong, M., D. Hirshleifer, S. Richardson and S.H. Teoh (2006), Does investor misvaluation drive the takeover market? *Journal of Finance* 61(2), 725-762.

Donkers, A.C.D., B. Melenberg and A.H.O. van Soest (2001), Estimating risk attitudes using lotteries: a large sample approach, *Journal of Risk and Uncertainty* 22, 165-195.

Dougherty, M.R.P. (2001), Integration of the ecological and error models of overconfidence using a multiple-trace memory model, *Journal of Experimental Psychology* 130(4), 579-599.

Douglas, G.W. (1969), Risk in equity markets: an empirical appraisal of market efficiency, *Yale Economic Essays*.

Doukas, J.A. and D. Petmezas (2007), Acquisitions, overconfident managers and self-attribution bias, *European Financial Management* 13(3), 531–577.

Downs, D.H. and Z.N. Güner (2000), Investment analysis, price formation and neglected firms: Does real estate make a difference? *Real Estate Economics* 28(4), 549-579.

Duesenberry, J.S. (1958), *Business cycles and economic growth*, Ed. McGraw Hill, New York.

Dufwenberg, M., T. Lindqvist and E. Moore (2005), Bubbles and experience: An experiment, *American Economic Review* 95(5), 1731–37.

Dumas, B., A. Kurshev and R. Uppal (2009), Equilibrium portfolio strategies in the presence of sentiment risk and excess volatility, *Journal of Finance* 64(2), 579-629.

Dunne, T., M.J. Roberts and L. Samuelson (1988), Patterns of firm entry and exit U.S. manufacturing industries, *Rand Journal of Economics* 19(4), 495-515.

Dunning, D., C. Heath and J.M. Suls (2004), Flawed self-assessment: Implications for health, education, and the workplace, *Psychological Science in the Public Interest* 5, 69-106.

Dunning, D., J.A. Meyerowitz and A.D. Holzberg (1989), Ambiguity and self-evaluation: The role of idiosyncratic trait definitions in self-serving assessments of others, *Journal of Personality and Social Psychology* 57, 1082-1090.

Dunning, D., K. Johnson, J. Ehrlinger and J. Kruger (2003), Why people fail to recognize their own incompetence, *Current Directions in Psychological Science* 12(3), 83-87.

Easley, D. and M. O'Hara (1987), Price, trade size, and information in security prices, *Journal of Financial Economics* 19(1), 69-90.

Eckmann, J.-P. and D. Ruelle (1985), Ergodic theory of chaos and strange attractors, *Reviews of Modern Physics* 57(3), 617-656.

Edwards, W. (1968), Conservatism in human information processing, Reprinted short version in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Eichengreen, B. et al. (eds.) (2011), Rethinking Central Banking, *The Committee on International Economic and Policy Reform*, available at http://www.brookings.edu/reports/2011/09_ciepr_central_banking.aspx

Eichengreen, B., E. Prasad and R. Rajan (2011), Rethinking central banking, *VoxEu.org*, 20 September 2011. Available at http://www.voxeu.org/article/rethinking-central-banking

Einhorn, H.J. and R.M. Hogarth (1978), Confidence in judgment: Persistence of the illusion of validity, *Psychological Review* 85(5), 395-416.

Einhorn, H.J. and R.M. Hogarth (1986), Decision making under ambiguity, *Journal of Business* 59(4), Part 2: The Behavioral Foundations of Economic Theory (Oct., 1986), S225-S250.

El-Erian, M. and M. Kumar (1995), Emerging equity markets in middle eastern countries, *International Monetary Fund*, Middle Eastern & Research Departments, Working paper, WP/94/103.

El-Gamal, M.A. (1992), The rational expectations-n(ϵ) ϵ-equilibrium, *Social Science working paper nº 823*, California Institute of Technology.

Ellis, C. (1998), Lessons from the Warwick and Chateau Chambord. *The Future of Investment Management*. Charlottesville, VA: AIMR, 25–31.

Engle, R.F. (1982), Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation, *Econometrica* 50(4), 987-1008.

Engle, R.F. and C.W.J. Granger (1987), Co-integration and error correction: Representation, estimation, and testing, *Econometrica* 55, 251-276.

Ennis, R.M. and M.D. Sebastian (2002), The small-cap alpha myth, *Journal of Portfolio Management* 28(3), 11-16.

Epley, N. and T. Gilovich (2001), Putting adjustment back in the anchoring and adjustment heuristic: Differential processing of self-generated and experimenter-provided anchors, *Psychological Science* 12, 391-396.

Epley, N. and T. Gilovich (2006), The anchoring-and-adjustment heuristic: Why the adjustments are insufficient, *Psychological Science* 17(4), 311-318.

Epley, N. and T. Gilovich (2010), Anchoring unbound, *Journal of Consumer Psychology* 20(1), 20-24.

Epstein, L.G. and M. Schneider (2010), Ambiguity and asset markets, *Annual Review of Financial Economics* 2, 315-346.

Epstein, L.G. and S.E. Zin (1990), First-order risk aversion and the equity premium puzzle, *Journal of Monetary Economics* 26, 387–407.

Erev, I., T.S. Wallsten and D.V. Budescu (1994), Simultaneous over- and underconfidence: The role of error in judgment processes, Psychological Review 10(3), 519-527.

European Banking Authority, EBA (2011), *2011 EU-Wide Stress Test*, available at www.eba.europa.eu

Ezekiel, M. (1938), The Cobweb theorem, *Quarterly Journal of Economics* 52(2), 255–280.

Fahlenbrach, R. and R.M. Stulz (2011), Bank CEO incentives and the credit crisis, *Journal of Financial Economics* 99(1), 11-26.

Falk, A., E. Fehr and U. Fischbacher (2003), On the nature of fair behavior, *Economic Inquiry* 41(1), 20-26.

Fama, E.F. (1965a), Random walks in stock market prices, *Financial Analysis Journal* 21 (5), 55-59.

Fama, E.F. (1965b), The behavior of stock market prices, *Journal of Business* 38 (1), 34-105.

Fama, E.F. (1970), Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25(2), 383-417.

Fama, E.F. (1984), Forward and spot exchange rates, *Journal of Monetary Economics* 14, 319-338.

Fama, E.F. (1985), What’s different about banks? *Journal of Monetary Economics* 15(1), 29-39.

Fama, E.F. (1990), Stock returns, expected returns, and real activity, *The Journal of Finance* 45(4), 1089-1108.

Fama, E.F. (1991), Efficient capital markets: II, *The Journal of Finance* 46 (5), 1575-1617.

Fama, E.F. (1998), Market efficiency, long-term returns and behavioral finance, *Journal of Financial Economics* 49(3), 283-306.

Fama, E.F. and G.W. Schwert (1977), Asset returns and inflation, *Journal of Financial Economics* 5, 115-146.

Fama, E.F. and J.D. MacBeth (1973). Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81 (3), 607–636.

Fama, E.F. and K.R. French (1988a), Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.

Fama, E.F. and K.R. French (1988b), Dividend yields and expected stock returns, *Journal of Financial Economics* 22(1), 3-25.

Fama, E.F. and K.R. French (1989), Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25(1), 23-49.

Fama, E.F. and K.R. French (1992), The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, E.F. and K.R. French (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, E.F. and K.R. French (1996), Multifactor explanations of asset pricing anomalies, *The Journal of Finance* 60(1), 55-84.

Fama, E.F. and K.R. French (2008), Dissecting anomalies, *Journal of Finance* 63(4), 1653-78.

Fama, E.F. and K.R. French (2012), Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105(3), 457-472.

Fama, E.F. and M. Blume (1966), Filter rules and stock market trading, *Journal of Business* 39 (1), 226-241.

Fama, E.F. and R.R. Bliss (1987), The information in long-maturity forward rates, *American Economic Review* 77, 680-692.

Fama, E.F., L. Fisher, M. Jensen and R. Roll (1969), The adjustment of stock prices to new information, *International Economic Review* 10 (1), 1-21.

Fare, R., S. Grosskopf and C.A.K. Lovell (1994), *Production frontiers*, Cambridge University Press, Oxford.

Farhi, E. and J. Tirole (2012), Bubbly liquidity, *Review of Economic Studies* 79, 678-706.

Farrell, M.J. (1957), The measurement of productive efficiency, *Journal of the Royal Statistical Society*, Series A, 120(3), 253-290.

Fehr, E. and A. Falk (1999), Wage rigidities in a competitive incomplete contract market, *Journal of Political Economy* 107, 106-134.

Feige, E.L. and D.K. Pearce (1976), Economically rational expectations: are innovations in the rate of inflation independent of innovations in the measures of monetary and fiscal policy? *Journal of Political Economy* 84 (3), 499-522.

Fellner, G. and S. Krüger (2012), Judgmental overconfidence: Three measures, one bias? *Journal of Economic Psychology* 33, 142-154.

Fellner, W. (1961), Distortion of subjective probabilities as a reaction to uncertainty, *Quarterly Journal of Economics* 75, 670-690.

Fernandez, R. and D. Rodrik (1991), Resistance to reform: Status quo bias in the presence of individual-specific uncertainty, *The American Economic Review* 81(5), 1146-55.

Festinger, L. (1957), *A Theory of Cognitive Dissonance*, Stanford University Press.

Festinger, L. and J.M. Carlsmith (1959), Cognitive consequences of forced compliance, *Journal of Abnormal and Social Psychology* 49(4, Part 1), 513-522.

Festinger, L., H.W. Riecken and S. Schachter (1956), *When Prophecy Fails*, University of Minnesota Press.

Fidmuc, J.P., M. Goergen and L. Renneboog (2006), Insider trading, news releases, and ownership concentration, *Journal of Finance* 61(6), 2931-2973.

Figlewski, S. (1979), Subjective information and market efficiency in a betting market, *Journal of Political Economy* 87, 75-88.

Finucane, M.L., A. Alhakami, P. Slovic and S.M. Johnson (2000), The affect heuristic in judgments of risks and benefits, *Journal of Behavioral Decision Making* 13(1), 1-17.

Fiordelisi, F. (2004), The profit-structure relationship accounting for technical and allocative efficiency: An application to the Italian factoring industry, *Bangor Business School Staff Publication and Working Papers*.

Fischhoff, B. (1982a), Debiasing, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Fischhoff, B. (1982b), For those condemned to study the past: Heuristics and biases in hindsight, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Fischhoff, B., P. Slovic and S. Lichtenstein (1977), Knowing with certainty: The appropriateness of extreme confidence, *Journal of Experimental Psychology: Human Perception and Performance* 3(4), 552-564.

Fishburn, P.C. and G.A. Kochenberger (1979), Two-piece von Neumann Morgenstern utility functions, *Decision Science* 10, 503-518.

Flavin, M.A. (1983), Excess volatility in the financial markets: A reassessment of the empirical evidence, *Journal of Political Economy* 91, 929-956.

Foster, G., C. Olsen and T. Shevlin (1984), Earnings releases, anomalies, and the behavior of security returns, *Accounting Review* 59(4), 574-603.

Frankel, J. and K. Froot (1988), Explaining the demand for dollars: International rates of return and the expectations of chartists and fundamentalists, In R. Chambers and P. Paarlberg (eds.), *Agriculture, Macroeconomics and the Exchange Rate*, Westfield Press.

Frankfurter, G.M., E.G. McGoun and D.E. Allen (2004), The prescriptive turn in Behavioral Finance, *Journal of Socio-Economics* 33, 449-468.

Frazzini, A. (2006), The disposition effect and underreaction to news, *Journal of Finance* 61, 2017-46.

Freixas, X. and J-C. Rochet (1998), *Microeconomics of Banking*, The MIT Press, Cambridge, Mass., 3rd edition.

French, K.R. (1980), Stock returns and the weekend effect, *Journal of Financial Economics* 8(1), 55-69.

French, K.R. and J. Poterba (1991), Investor diversification and international equity markets, *American Economic Review* 81, 222-226.

French, K.R. and R. Roll (1986), Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17(1), 5-26.

French, K.R., G.W. Schwert and R.F. Stambaugh (1987), Expected stock returns and volatility, *Journal of Financial Economics* 19, 3-29.

Freud, S. (1958), Beyond the Pleasure Principle, In J. Strachey and A. Freud, *The Standard Edition of the Complete Psychological Works of Sigmund Freud*, Hogarth.

Friedman, H.H. and L.W. Friedman (2009), The global financial crisis of 2008: What went wrong? Available at SSRN: http://dx.doi.org/10.2139/ssrn.1356193

Friedman, M. (1953a), The case for flexible exchange rates, In: *Essays in Positive Economics*, University of Chicago Press, 157-203.

Friedman, M. (1953b), *Essays in Positive Economics*, University of Chicago Press.

Friend, I., M. Blume and J. Crockett (1970), *Mutual funds and other institutional investors*, McGraw Hill.

Fries, S. and A. Taci (2005), Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries, *Journal of Banking and Finance* 29, 55-81.

Froot, K.A. and E. Dabora (1999), How are stock prices affected by the location of trade? *Journal of Financial Economics* 53, 189-216.

Froot, K.A. and R.H. Thaler (1990), Anomalies: Foreign exchange, *Journal of Economic Perspectives* 4, 179-192.

Gabaix, X., P. Gopikrishnan, V. Plerou and H.E. Stanley (2006), Institutional investors and stock market volatility, *Quarterly Journal of Economics* 121(2), 461-504.

Gallo, G., C.W. Granger and Y. Jeon (2002), Copycats and common swings: The impact of the use of forecasts in information sets, *IMF Staff Papers* 49, 1–18.

Gangopadhyay, P. (1996), Macroeconomic variables and seasonal mean reversion in stock returns, *Journal of Financial Research* 19, 395-416.

Gaunt, C., P. Gray and J. Mclvor (2000), The impact of share price on seasonality and size anomalies in Australian equity markets, *Accounting and Finance* 40(1), 33-50.

Gennaioli, N. and A. Shleifer (2010), What comes to mind, *The Quarterly Journal of Economics* 125(4), 1399-1433.

Geroski, P.A., J. Mata and P. Portugal (2010), Founding conditions and the survival of new firms, *Strategic Management Journal* 31, 510-529.

Gervais, S. and I. Goldstein (2004), Overconfidence and team coordination, *Working Paper*, Wharton School – University of Pennsylvania.

Gervais, S. and T. Odean (2001), Learning to be overconfident, *Review of Financial Studies* 14, 1-27

Gervais, S., J.B. Heaton and T. Odean (2011), Overconfidence, compensation contracts, and capital budgeting, *Journal of Finance* 66(5), 1735-77.

Gettys, C.F., C. Kelly III and C.R. Peterson (1973), The best-guess hypothesis in multistage inference, *Organizational Behavior and Human Performance* 10, 364-373.

Gigerenzer, G. (1991), How to make cognitive illusions disappear: Beyond 'heuristics and biases', In W. Stroebe and M. Hewstone (eds.), *European Review of Social Psychology*, Wiley.

Gigerenzer, G. (1996), On narrow norms and vague heuristics: A rebuttal to Kahneman and Tversky (1996), *Psychological Review* 103, 592-596.

Gigerenzer, G. (2001), The adaptive toolbox: Toward a Darwinian rationality, In F.A. French, A.C. Kamil, and D.W. Leger (eds.), *Evolutionary Psychology and Motivation*, Nebraska Symposium on Motivation 48, 113-143, University of Nebraska Press.

Gigerenzer, G. and D.G. Goldstein (1996), Reasoning the fast and frugal way: Models of bounded rationality, *Psychological Review* 103(4), 650-669.

Gigerenzer, G. and D.G. Goldstein (1999), Betting on one good reason: The take the best heuristic, In Gigerenzer, G., P.M. Todd and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, Oxford University Press.

Gigerenzer, G. and D.G. Goldstein (2011), The recognition heuristic: A decade of research, *Judgment and Decision Making* 6(1), 100-121.

Gigerenzer, G. and R. Selten (2001), Bounded rationality: The adaptive toolbox, *Dahlem Workshop Reports*, The MIT Press.

Gigerenzer, G. and W. Gaissmaier (2011), Heuristic decision making, *Annual Review of Psychology* 62, 451-482, available at SSRN: http://ssrn.com/abstract=1722019

Gigerenzer, G., P.M. Todd and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, Oxford University Press.

Gigerenzer, G., U. Hoffrage and H. Kleinbölting (1991), Probabilistic mental models: A Brunswikian theory of confidence, *Psychological Review* 98, 506–528.

Gilbert, P., J. Price and S. Allan (1995), Social comparison, social attractiveness and evolution: How might they be related? *New Ideas in Psychology* 13(2), 149-165.

Gilovich, T. (1991), *How we know what isn't so: The fallibility of human reason in everyday life*, New York: The Free Press.

Gilovich, T. and D. Griffin (2002), Introduction – Heuristics and Biases: Then and now, In T. Gilovich, D. Griffin and D. Kahneman (eds.), *Heuristics and biases: The psychology of intuitive judgment*, Cambridge University Press.

Gilovich, T., D. Griffin and D. Kahneman (2002), *Heuristics and biases: The psychology of intuitive judgment*, Cambridge University Press.

Gilovich, T., V.H. Medvec and D. Kahneman (1998), Varieties of regret: A debate and partial resolution, *Psychological Review* 105(3), 602-605.

Givoly, D. (1985), The formation of earnings expectations, *The Accounting Review* 60 (3), 372-386.

Glimcher, P.W., M.C. Dorris and H.M. Bayer (2005), Physiological utility theory and the neuroeconomics of choice, *Games and Economic Behavior* 52, 213–256.

Godfrey, M.D., C.W.J. Granger and O. Morgenstern (1964), The random walk hypothesis on stock market behavior, *Kyklos* 18, 1-30.

Godlewski, C.J. (2012), Are bank loans still 'special' (especially during a crisis)? Empirical evidence from a European country, *19th Annual Conference of the Multinational Finance Society, Krakow*, June 2012.

Goette, L., D. Huffman and E. Fehr (2004), Loss aversion and labour supply, *Journal of the European Economic Association* 2, 216-228.

Goetzmann, W.N. and A. Kumar (2008), Equity portfolio diversification, *Review of Finance* 12, 433-463. Also circulated as Goetzmann, W. and A. Kumar (2004), Why do individual investors hold under-diversified portfolios? NBER Working Paper 8686.

Goetzmann, W.N. and N. Peles (1997), Cognitive dissonance and mutual fund investors, *Journal of Financial Research* 20(2), 145-158.

Goldstein, D.G. and G. Gigerenzer (1999). The recognition heuristic: How ignorance makes us smart, In G. Gigerenzer, P.M. Todd, and the ABC Research Group, *Simple Heuristics That Make Us Smart*, New York: Oxford University Press, pp. 37–58.

Goldstein, D.G. and G. Gigerenzer (2002). Models of ecological rationality: The recognition heuristic. *Psychological Review* 109, 75–90.

Goldstein, W.M. and H.J. Eihorn (1987), Expression theory and the preference reversal phenomena, *Psychological Review* 94, 236-254.

Gomes, J.F. and L. Schmid (2010), Levered returns, *Journal of Finance* 65(2), 467-494.

Gonzalez, R. and G. Wu (1999), On the shape of the probability weighting function, *Cognitive Psychology* 38(1), 129-166.

Gonzalez, R. and G. Wu (2003), Composition rules in original and cumulative prospect theory, *Mimeo*, Avail. at http://faculty.chicagobooth.edu/george.wu/research/papers/CompositionRules.pdf

Graham, B. and D. Dodd (1934), *Security analysis*, McGraw-Hill.

Graham, J.W. (2009), Missing data analysis: Making it work in the real world, *Annual Review of Psychology* 60, 549-576.

Granger, C.W.J. (1992), Forecasting stock market prices: lessons for forecasters, *International Journal of Forecasting* 8, 3-13.

Granger, C.W.J. and O. Morgenstern (1963), Spectral analysis of New York Stock Market prices, *Kyklos* 16, 1-27.

Granger, C.W.J. and O. Morgenstern (1970), *Predictability of stock market prices*, Lexington, Mass.: Heath Lexington Books.

Gredler, M.E. (2004), Games and simulations and their relationships to learning, *Handbook of research on educational communications and technology* 2, 571-581.

Greenberg, J. (1983), Overcoming egocentric bias in perceived fairness through self-awareness, *Social Psychology* 46(2), 152-156.

Greene, W. (2005), Reconsidering heterogeneity in panel data estimators of the stochastic frontier model, *Journal of Econometrics* 126, 269-303.

Greenwald, B.C. and J.E. Stiglitz (1986), Externalities in economies with imperfect information and incomplete markets, *Quarterly Journal of Economics* 101, 229-64.

Greenwald, B.C., J.E. Stiglitz and A. Weiss (1985), Informational imperfections in the capital market and macro-economic fluctuations, *American Economic Review* 74(1), 194-99.

Grieco, D. and R.M. Hogarth (2009), Overconfidence in absolute and relative performance: The regression hypothesis and Bayesian updating, *Journal of Economic Psychology* 30(5), 756-771

Griffin, D. and A. Tversky (1992), The weighing of evidence and the determinants of confidence, *Cognitive Psychology* 24(3), 411-435.

Griffin, D. and L. Brenner (2004), Perspectives on probability judgment calibration, In D.J. Koehler and N. Harvey (eds.), *Blackwell Handbook of Judgment and Decision Making*, pp. 177-199.

Griffin, J.M., J. Harris and S. Topaloglu (2003), Investor behavior over the rise and fall of Nasdaq, *Working paper*, Yale University.

Griffin, J.M., X. Ji and J.S. Martin (2003), Momentum investing and business cycle risk: evidence from pole to pole, *Journal of Finance*, 2515–2547.

Griffith, R.M. (1949), Odds adjustments by American horse-race bettors, *The American Journal of Psychology* 62(2), 290-294.

Grinblatt, M. and B. Han (2005), Prospect theory, mental accounting, and momentum, *Journal of Financial Economics* 78(2), 311-339.

Grinblatt, M. and M. Keloharju (2001), What makes investors trade? *Journal of Finance* 56(2), 589-616.

Grinblatt, M. and M. Keloharju (2004), Tax-loss trading and wash sales, *Journal of Financial Economics* 71(1), 51-76.

Grinblatt, M. and M. Keloharju (2009), Sensation seeking, overconfidence and trading activity, *The Journal of Finance* 64(2), 549-578.

Grinblatt, M. and S. Titman (1992), The persistence of mutual fund performance, *Journal of Finance* 47(5), 1977-1984.

Grinblatt, M., R.W. Masulis and S. Titman (1984), The valuation effects of stock splits and stock dividends, *Journal of Financial Economics* 13(4), 461-490.

Grinblatt, M., S. Titman and R. Wermers (1995), Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *The American Economic Review* 85(5), 1088-1105.

Gromb, D. and D. Vayanos (2002), Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics* 66, 361-407.

Gropp, J. (2004), Mean reversion of industry stock returns in the U.S., 1926–1998, *Journal of Empirical Finance* 11(4), 527-551.

Grossman, S.J. (1976), On the efficiency of competitive stock markets where traders have diverse information, *Journal of Finance* 31(2), 573-585.

Grossman, S.J. and J.E. Stiglitz (1976), Information and competitive price systems, *American Economic Review* 66(2), 246-253.

Grossman, S.J. and J.E. Stiglitz (1980), On the impossibility of informationally efficient markets, *American Economic Review* 70(3), 393-408.

Grossman, S.J. and O. Hart (1986), The costs and benefits of ownership: A theory of vertical and lateral integration, *Journal of Political Economy* 94, 691-719.

Grossman, S.J. and R.J. Shiller (1981), The determinants of the variability of stock market prices, *American Economic Review* 71(2), 222-227.

Grunberg, E. and F. Modigliani (1954), The predictability of social events, *Journal of Political Economy* 62, 456-470.

Grundy, B.D. and J.S. Martin (2001), Understanding the nature of the risks and the source of the rewards to momentum investing, *Rodney L. White Center for Financial Research Working Paper Series* 13-98.

Gu, A.Y. (2003), The declining January effect: Evidences from the U.S. equity markets, *Quarterly Review of Economics and Finance* 43(2), 395-404.

Gu, F. and J.Q. Li (2007), The credibility of voluntary disclosure and insider stock transactions, *Journal of Accounting Research* 45(4), 771-810.

Guiso, L., P. Sapienza and L. Zingales (2006), Does culture affect economic outcomes? *Journal of Economic Perspectives* 20(2), 23-48.

Gul, F. (1991), A theory of disappointment aversion, *Econometrica* 59(3), 667-686.

Güth, W., R. Schmittberger and B. Schwarze (1982), An experimental analysis of ultimatum bargaining, *Journal of Economic Behavior and Organization* 3, 367-388.

Gwynne, S. (1986), *Selling money*, Weidenfeld and Nicholson.

Hadar, J. and W.R. Russell (1969), Rules for ordering uncertain prospects, *The American Economic Review* 59(1), 25-34.

Hall, B.J. and K.J. Murphy (2000), Optimal exercise prices for executive stock options, *American Economic Review* 90, 209-214

Hall, B.J. and K.J. Murphy (2002), Stock options for undiversified executives, *Journal of Accounting and Economics* 33, 3-42.

Haltiwanger, J. and M. Waldman (1985), Rational expectations and the limits of rationality: An analysis of heterogeneity, *American Economic Review* 75(3), 326-340.

Hamilton, J.D. (1988), Rational-expectations econometric analysis of changes in regime. An investigation of the term structure of interest rates, *Journal of Economic Dynamics and Control* 12, 385-423.

Hanemann, W.M. (1991), Willingness to pay and willingness to accept: How much can they differ? *American Economic Review* 81, 635–647.

Hansen, L.P. (1982), Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029-54.

Hansen, L.P. and K.J. Singleton (1982), Generalized instrumental variable estimation of nonlinear rational expectations models, *Econometrica* 50(5), 1269-86.

Hansen, L.P. and K.J. Singleton (1983), Stochastic consumption, risk aversion, and the temporal behavior of asset prices, *Journal of Political Economy* 91(2), 249-265.

Hansen, L.P. and R. Jagannathan (1991), Implications of security market data for models of dynamic economies, *Journal of Political Economy* 99 (2), 225-262.

Hanson, P., M. Ronnlund, P. Juslin and L.G. Nilsson (2008), Adult age differences in the realism of confidence judgments: Overconfidence, format dependence, and cognitive predictors, *Psychology and Aging* 23(3), 531-544.

Hanvanich, S. and S.T. Çavusgil (2001), Stock market reactions to international joint venture announcement: An event analysis, *International Business Review* 10(2), 139-154.

Hardie, B.G.S., E.J. Johnson and P.S. Fader (1993), Modeling loss aversion and reference dependence effects on brand choice, *Marketing Science* 12, 378-394.

Harris, L.E. and V. Panchapagesan (2005), The information content of the limit order book: Evidence from NYSE specialist trading decisions, *Journal of Financial Markets* 8(1), 25-67.

Harrison, G.W. (2008), Neuroeconomics: A critical reconsideration, *Economics and Philosophy* 24(3), 303-344.

Harrison, G.W. and E. Rutström (2009), Expected utility theory and prospect theory: One wedding and a decent funeral, *Experimental Economics* 12(2), 133-158.

Harrison, G.W. and J.A. List (2004), Field experiments, *Journal of Economic Literature* 42, 1009-55.

Harrison, M. and D.M. Kreps (1978), Speculative investor behavior in a stock market with heterogeneous expectations, *The Quarterly Journal of Economics* 92(2), 323-336.

Harsanyi, J.C. (1967), Games with incomplete information played by bayesian players: Part I, *Managerial Sciences* 14 (3), 159-182.

Hart, O. and J. Moore (1994), A theory of debt based on the inalienability of human capital, *Quarterly Journal of Economics* 109, 841-879.

Hart, O. and J. Moore (1998), Default and renegotiation: A dynamic model of debt, *Quarterly Journal of Economics* 113, 1-42.

Hartman, R., M. Doane and C. Woo (1991), Consumer rationality and the status quo, *Quarterly Journal of Economics* 106(1), 141-162.

Hassan, K.M., M. Haque and S. Lawrence (2006), An empirical analysis of emerging stock markets of Europe, *Quarterly Journal of Business and Economics* 45, 31-52.

He, H. and J. Wang (1995), Differential information and dynamic behavior of stock trading volume, *The Review of Financial Studies* 8(4), 919-972.

Heath, C., R.P. Larrick and G. Wu (1999), Goals as reference points, *Cognitive Psychology* 38, 79–109.

Heath, C., R.P. Larrick and J. Klayman (1998), Cognitive repairs: How organizational practices can compensate for individual shortcomings, *Research in Organizational Behavior* 20, 1-37.

Heaton, J. (2002), Managerial optimism and corporate finance, *Financial Management* 31(2), 33-45.

Hellwig, M.F. (1980), On the aggregation of information in competitive markets, *Journal of Economic Theory* 22(3), 477-498.

Hellwig, M.F. (1991), Banking, financial intermediation and corporate finance, In A. Giovannini and C. Mayer (eds.), *European Financial Integration*, Cambridge: Cambridge University Press.

Helson, H. (1964), *Adaptation level theory: An experimental and systematic approach to behavior*, Harper & Row.

Hendricks, D., J.M. Patel and R. Zeckhauser (1993), Hot hands in mutual funds: Short-run persistence of relative performance, 1974-1988, *Journal of Finance* 48(1), 93-130.

Henrich, J., R. Boyd, S. Bowles, C. Camerer, H. Gintis, R. McElreath and E. Fehr (2001), In search of Homo economicus: Behavioral experiments in 15 small-scale societies, *American Economic Review* 91(2), 73-79.

Hens, T. and K. Bachmann (2008), *Behavioral Finance for Private Banking*, John Wiley & Sons.

Hens, T. and M.O. Rieger (2010), *Financial economics: A concise introduction to classical and behavioral finance*, Springer.

Hershfield, H.E., D.G. Goldstein, W.F. Sharpe, J. Fox, L. Yeykelis, L.L. Carstensen and J.N. Bailenson (2011), Increasing saving behavior through age-progressed renderings of the future self, *Journal of Marketing Research* 68, S23–S37.

Hicks, J.R. (1935), Annual survey of economic theory: The theory of monopoly, *Econometrica*.

Himmelberg, C.P. and D.P. Morgan (1995), Is bank lending special? in J. Peek and E.S. Rosengren (eds.) *Is Bank Lending Important for the Transmission of Monetary Policy?* FRB Boston Conference Series no.39, 15-36.

Hinds, P.J. (1999), The curse of expertise: The effects of expertise and debiasing methods on predictions of novice performance, Journal of Experimental Psychology: Applied 5(2), 205-221.

Hinich, M.J. and D.M. Patterson (1985), Evidence of nonlinearity in daily stock returns, *Journal of Business and Economic Statistics* 3(1), 69-77.

Hinich, M.J. and D.M. Patterson (1989), Evidence of nonlinearity in the trade-by-trade stock market return generating process, In W.A. Barnett, J. Geweke and K. Shell (eds.), *Economic complexity: Chaos, sunspots, bubbles and nonlinearity*, Cambridge University Press, 383-409.

Hirshleifer, D. (2001), Investor psychology and asset pricing, *Journal of Finance* 56(4), 1533-97.

Hirshleifer, D. (2008), Psychological bias as a driver of financial regulation, *European Financial Management* 14(5), 856-874.

Hirshleifer, D. and S.H. Teoh (2003), Limited attention, information disclosure and financial reporting, *Journal of Accounting and Economics* 36(1), 337-386.

Hirshleifer, D., A. Subrahmanyam and S. Titman (2006), Feedback and the success of irrational traders, *Journal of Financial Economics* 81, 311–388.

Hodges, S.H., R.G. Tompkins and W.T. Ziemba (2008), The favorite longshot bias in S&P 500 and FTSE 100 Index futures options: The return to bets and the cost of insurance, in *Handbook of Sports and Lottery Markets*, Elsevier.

Hodrick, R. (1987), *The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets*, Harwood Academic.

Hoff, K. and J.E. Stiglitz (2010), Equilibrium fictions: A cognitive approach to societal rigidity, *American Economic Review* 100(2), 141-146.

Hoff, K. and J.E. Stiglitz (2011), The role of cognitive frames in societal rigidity and change, *World Bank*. http://www.ewi-ssl-pitt.edu/econ/files/seminars/110405_sem814_Karla%20Hoff.pdf

Hoff, K. and P. Priyanka (2004), Belief systems and durable inequalities: An experimental investigation of Indian caste, *World Bank Working Paper 3351*.

Hoffrage, U. and R. Hertwig (1999), Hindsight Bias: A price worth paying for fast and frugal memory, In G. Gigerenzer, P.M. Todd and the ABC Research Group, *Simple Heuristics That Make Us Smart*, Oxford University Press.

Hoffrage, U., R. Hertwig and G. Gigerenzer (2000), Hindsight bias: A by-product of knowledge updating? *Journal of Experimental Psychology: Learning, Memory and Cognition* 26(3), 566-581.

Hong, H. and J.C. Stein (1999), A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54(6), 2143-84.

Hong, H., J. Kubik and A. Solomon (2000), Security analysts' career concerns and herding of earnings forecasts, *Rand Journal of Economics* 31, 121–44.

Hong, H., J. Kubik and J.C. Stein (2005), Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers, *Journal of Finance* 60, 2801–24.

Hong, H., J. Scheinkman and W. Xiong (2006), Asset float and speculative bubbles, *Journal of Finance* 61, 1073–1117.

Hong, H., T. Lim and J.C. Stein (2000), Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55(1), 265-295.

Horowitz, J.K. and K.E. McConnell (2003), Willingness to accept, willingness to pay and the income effect, *Journal of Economic Behavior and Organization* 51, 537-545.

Hou, K., G.A. Karolyi and B.-C. Kho (2011), What factors drive global stock returns? *Review of Financial Studies* 24(8), 2527-74.

Howitt, D. and D. Cramer (2008), *Introduction to Research Methods in Psychology*, Essex: Pearson Education, 2nd ed.

Huang, S-Y, N. Lambertides and J.M. Steeley (2012), Cash hoards and managerial overconfidence, *19th Annual Conference of the Multinational Finance Society*, Krakow, June 2012.

Huberman, G. (2001), Familiarity breeds investment, *The Review of Financial Studies* 14(3), 659-680.

Hughes, J. and C.-G. Moon (1995), Measuring bank efficiency when managers trade return for reduced risk, *Working paper 1995-20*, Department of Economics, Rutgers University.

Hughes, J. and L.J. Mester (1993), A quality and risk-adjusted cost function for banks: Evidence on the too-big-to-fail doctrine, *Journal of Productivity Analysis* 4, 293-315.

Hwang, S. and M. Salmon (2004), Market stress and herding, *Journal of Empirical Finance* 11(4), 585-616.

Ikenberry, D.L. and S. Rammath (2002), Underreaction to self-selected news events: The case of stock splits, *Review of Financial Studies* 15(2), 489-526.

Ikenberry, D.L., G. Rankine and E.K. Stice (1996), What do stock splits really signal? *Journal of Financial and Quantitative Analysis* 31(3), 357-375.

Ikenberry, D.L., J. Lakonishok and T. Vermaelen (1995), Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181-208.

IMF (2012), Spain – Financial system stability assessment, *Country Report No 12/137, International Monetary Fund*. Available at http://www.imf.org/external/pubs/ft/scr/2012/cr12137.pdf

Inman, J.J. and L. McAlister (1994), Do coupon expiration dates affect consumer behavior? *Journal of Marketing Research* 31, 423-428.

Jaffe, D.M. and T. Russell (1976), Imperfect information, uncertainty, and credit rationing, *The Quarterly Journal of Economics* 90(4), 651-666.

Jaffe, J. (1974a), Special information and insider trading, *Journal of Business* 47(3), 410-428.

Jaffe, J. (1974b), The effect of regulation changes on insider trading, *Bell Journal of Economics and Management Science* 5(1), 93-121.

Jaffe, J. and R. Westerfield (1985), The weekend effect in common stock returns: The international evidence, *Journal of Finance* 40(2), 433-454.

James, C. and R. Edmister (1983), The relation between common stock returns trading activity and market value, *Journal of Finance* 38(4), 1075-1086.

Janis, I.L. (1972), *Victims of Groupthink*, Houghton Mifflin.

Jegadeesh, N. (1990), Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N. (1991), Seasonality in stock price mean reversion: evidence from the U.S. and the U.K., *Journal of Finance* 46, 1427-44.

Jegadeesh, N. and S. Titman (1993), Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, N. and S. Titman (1995), Short-horizon return reversals and the bid-ask spread, *Journal of Financial Intermediation* 4, 116-132.

Jegadeesh, N. and S. Titman (2001), Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56(2), 699-720.

Jegadeesh, N. and W. Kim (2010), Do analyst herd? An analysis of recommendations and market reactions, *The Review of Financial Studies* 23(2), 901-937.

Jemaiel, S., C. Mamoghli and W. Seddiki (2013), An experimental analysis of over-confidence, *American Journal of Industrial and Business Management* 3, 395-417.

Jensen, M.C. (1969), Risk, the pricing of capital assets, and the evaluation of investment portfolios, *Journal of Business* 42(2), 167-247.

Jensen, M.C. (1978), Some anomalous evidence regarding market efficiency, *Journal of Financial Economics* 6, 95-101.

Jensen, M.C. and G.A. Bennington (1970), Random walks and technical theories: Some additional evidence, *Journal of Finance* 25, 469-482.

Jeong, B.-K. and A.C. Stylianou (2010), Market reaction to application service provider (ASP) adoption: An empirical investigation, *Information and management* 47(3), 176-187.

Ji, L.-J., R.E. Nisbett and Y. Su (2001), Culture, change, and prediction, *Psychological Science* 12(6), 450–456.

Johnson, B.T. and A.H. Eagly (1989), Effects of involvement on persuasion: A meta-analysis, *Psychological Bulletin* 106(2), 290-314.

Johnson, E.J. and D. Goldstein (2003), Do defaults save lives? *Science* 302(5649), 1338-39.

Jones, C.P. and R.H. Litzenberger (1970), Quarterly earnings reports and intermediate stock price trends, *Journal of Finance* 25(1), 143-148.

Jorda, O., M.H.P Schularick and A.M. Taylor (2011), When credit bites back: Leverage, business cycles, and crises, *National Bureau of Economic Research*, Inc, NBER Working Papers: 17621.

Jung, J. and R. Shiller (2006), Samuelson's dictum and the stock market, *Economic Inquiry* 43(2), 221-228.

Juslin, P. (1994), The overconfidence phenomenon as a consequence of informal experimenter-guided selection of almanac items, *Organizational Behavior and Human Decision Processes* 57(2), 226-246.

Juslin, P., A. Winman and H. Olsson (2000), Naive empiricism and dogmatism in confidence research: A critical examination of the hard-easy effect, *Psychological Review* 10, 384-396.

Kahneman, D. (1994), New challenges to the rationality assumption, *Journal of Institutional and Theoretical Economics* 150(1), 18-36.

Kahneman, D. (2003a), Maps of bounded rationality: Psychology for Behavioral Economics, *The American Economic Review* 93(5), 1449-75.

Kahneman, D. (2003b), A perspective on judgment and choice: Mapping bounded rationality, *American Psychologist* 58(9), 697-720.

Kahneman, D. (2011), *Thinking, fast and slow*, New York: Farrar, Strauss and Giroux, first edition.

Kahneman, D. and A. Tversky (1972), Subjective probability: A judgment of representativeness, *Cognitive Psychology* 3, 430-454.

Kahneman, D. and A. Tversky (1973), On the psychology of prediction, *Psychological Review* 80, 237-251.

Kahneman, D. and A. Tversky (1979), Prospect theory: An analysis of decision under risk, *Econometrica* 47(2), 263-292.

Kahneman, D. and A. Tversky (1982a), Intuitive Prediction: Biases and Corrective Procedures, In D. Kahneman, P. Slovic and A. Tversky, (eds.), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge Univ. Press.

Kahneman, D. and A. Tversky (1982b), The simulation heuristic, In D. Kahneman, P. Slovic and A. Tversky (eds.), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Kahneman, D. and A. Tversky (1982c), On the study of statistical intuitions, In D. Kahneman, P. Slovic and A. Tversky, (eds.), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Kahneman, D. and A. Tversky (1984), Choices, values and frames, *American Psychologist* 39, 341-350.

Kahneman, D. and A. Tversky (1996), On the reality of cognitive illusions, *Psychological Review* 103(3), 582-591.

Kahneman, D. and A. Tversky (2000), *Choices, Values, and Frames*, Cambridge University Press.

Kahneman, D. and D. Lovallo (1993), Timid choices and bold forecasts: A cognitive perspective on risk taking, *Management Science* 39(1), 17-31.

Kahneman, D. and M. Riepe (1998), Aspects of investor psychology, *Journal of Portfolio Management* 24, 52-65.

Kahneman, D. and S. Frederick (2002), Representativeness revisited: Attribute substitution in intuitive judgment, in T. Gilovich, D. Griffin and D. Kahneman (eds.), *Heuristics and biases: The psychology of intuitive thought*, Cambridge University Press, pp. 49-81.

Kahneman, D. and S. Frederick (2005), A model of heuristic judgment, in K.J. Holyoake and R.G. Morrison (eds.) *The Cambridge Handbook of Thinking and Reasoning*, Cambridge University Press.

Kahneman, D., J.L. Knetsch and R.H. Thaler (1986a), Fairness as a constraint on profit seeking: Entitlements in the market, *American Economic Review* 76(4), 728-741.

Kahneman, D., J.L. Knetsch and R.H. Thaler (1986b), Fairness and the assumptions of Economics, *Journal of Business* 59(4), S285-S300.

Kahneman, D., J.L. Knetsch and R.H. Thaler (1990), Experimental tests of the endowment effect and the Coase Theorem, *Journal of Political Economy* 98(6), 1325-48.

Kahneman, D., J.L. Knetsch and R.H. Thaler (1991), Anomalies: The endowment effect, loss aversion, and status quo bias, *The Journal of Economic Perspectives* 5(1), 193-206.

Kahneman, D., P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Kamas, L. and A. Preston (2012), The importance of being confident; gender, career choice, and willingness to compete, *Journal of Economic Behavior and Organization* 83, 82-97.

Kandel, E. and N.D. Pearson (1995), Differential interpretation of public signals and trade in speculative markets, *Journal of Political Economy* 103(4), 831-872.

Karas, A., K. Schoors and L. Weill (2010), Are private banks more efficient than public banks? Evidence from Russia, *Economics of Transition* 18(1), 209-244.

Karmakar, U.S. (1978), Subjectively weighted utility: A descriptive extension of the expected utility model, *Organizational Behavior and Human Performance* 24, 67-72.

Karolyi, G.A. and B.-C. Kho (2004), Momentum strategies: Some bootstrap tests, *Journal of Empirical Finance* 11(4), 509-536.

Kasa, K., T.B. Walker and C.H. Whiteman (2006), Asset prices in a time series model with perpetually disparately informed, competitive traders, *CAEPR Working Papers No. 2006-010*.

Katona, G. (1901), *Psychological Economics*, Elsevier (1975).

Kaufmann, S. and M.T. Valderrama (2008), Bank lending in Germany and the UK: Are there differences between a bank-based and a market-based country? *International Journal of Finance and Economics* 13, 266-279.

Kaul, G. and M. Nimalendran (1990), Price reversals: Bid-ask errors or market overreaction? *Journal of Financial Economics* 28, 67-93.

Kausar, A. and R. Taffler (2006), Testing behavioral finance models of market under and overreaction: Do they really work? *Working Paper,* University of Edinburgh, Available at SSRN: http://ssrn.com/abstract=873615

Kaustia, M. and M. Perttula (2012), Overconfidence and debiasing in the financial industry, *Review of Behavioral Finance* 4(1), 46-62.

Ke, B., S. Huddart and K, Petroni (2003), What insiders know about future earnings and how they use it: Evidence from insider trades, *Journal of Accounting and Economics* 35(3), 315-346.

Keen, S. (2011), A monetary Minsky model of the Great Moderation and the Great Recession, *Journal of Economic Behavior & Organization*, http://dx.doi.org/10.1016/j.jebo.2011.01.010

Keim, D.B. (1983), Size-related anomalies and stock return seasonality: further empirical evidence, *Journal of Financial Economics* 12(1), 13-32.

Keim, D.B. (1986), The CAPM and equity return regularities, *Financial Analysts Journal* 42(3), 19-34.

Keim, D.B. and R.F. Stambaugh (1986), Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357-390.

Kendall, M.G. (1953), The analysis of economic time series, part I: Prices, *Journal of the Royal Statistical Society, Series A*, 116(1), 11-25.

Keren, G. (1987), Facing uncertainty in the game of bridge: A calibration study, *Organizational Behavior & Human Decision Processes* 39(1), 98-114.

Keynes, J.M. (1936), *The General Theory of Employment, Interest and Money*, London: MacMillan.

Keys, B.J., T. Mukherjee, A. Seru and V. Vig (2010), Did securitization lead to lax screening? Evidence from subprime loans, *Quarterly Journal of Economics* 125(1), 307-362.

Kim, M., C. Nelson and R. Startz (1991), Mean reversion in stock prices? A reappraisal of the empirical evidence, *Review of Economic Studies* 58, 515-528.

Kindleberger, C.P. (1978), *Manias, Panics and Crashes: A History of Financial Crises*, New York: Palgrave Macmillan, sixth edition, 2011.

Kirby, K.N. and R.J. Herrnstein (1995), Preference reversals due to myopic discounting of delayed reward, *Psychology Science* 6(2), 83-89.

Kirchler, M., J. Huber and T. Stockl (2011), Thar she bursts: Reducing confusion reduces bubbles, *Working Papers in Economics and Statistics*, University of Innsbruck.

Kiyotaki, N. and J. Moore (1997), Credit cycles, *Journal of Political Economy* 105(2), 211-248.

Klayman, J., J. Soll, C. Gonzalez-Vallejo and S. Barlas (1999), Overconfidence: It depends on how, what, and whom you ask, *Organizational Behavior and Human Decision Processes* 79, 216-247.

Kleidon, A.W. (1986), Variance bounds tests and stock price valuation models, *Journal of Political Economy* 94, 953-1001.

Klein, R.W. and V.S. Bawa (1977), The effect of limited information and estimation risk on optimal portfolio diversification, *Journal of Financial Economics* 5, 89-111.

Knetsch, J.L. (1989), The endowment effect and evidence of nonreversible indifference curves, *The American Economic Review* 79(5), 1277-84.

Knetsch, J.L. and J.A. Sinden (1984), Willingness to pay and compensation demanded: Experimental evidence of an unexpected disparity in measures of value, *Quarterly Journal of Economics* 99(3), 507-521.

Köbberling, V. and P. Wakker (2005), An index of loss aversion, *Journal of Economic Theory* 122, 119-131.

Kocherlakota, N. (2009), Bursting bubbles: Consequences and cures, Minneapolis Fed., *Macroeconomic and Policy Challenges Following Financial Meltdowns Conference*, April 3rd, 2009.

Kodres, L.E. and M. Pritsker (2002), A rational expectations model of financial contagion, *Journal of Finance* 57 (2), 769-799.

Kolari, J., A. Mahajan and E.M. Saunders (1988), The effect of changes in reserve requirements on bank stock prices, *Journal of Banking and Finance* 12(2), 183-198.

Kon, S.J. and F.C. Jen (1978), Estimation of time-varying systematic risk and performance for mutual fund portfolios: An application of switching regression, *Journal of Finance* 33(2), 457-475.

Koriat, A., S. Lichtenstein and B. Fischhoff (1980), Reasons for confidence, *Journal of Experimental Psychology: Human Learning and Memory* 6(2), 107-118.

Kõszegi, B. and M. Rabin (2006), A model of reference-dependent preferences, *Quarterly Journal of Economics* 121(4), 1133-65.

Kõszegi, B. and M. Rabin (2007), Reference-dependent risk attitudes, *The American Economic Review* 97(4), 1047-73.

Kothari, S. and J. Shanken (1997), Book.to-market, dividend yield and expected market returns: a time series analysis, *Journal of Financial Economics* 46, 169-203.

Koutsomanoli-Filippaki, A., D. Margaritis and Ch. Staikouras (2009), Efficiency and productivity growth in the banking industry of Central and Eastern Europe, *Journal of Banking and Finance* 33, 557-567.

Kraay, A. and J. Ventura (2007), The dot-com bubble, the Bush deficits, and the US current account, In R. Clarida (ed.), *G7 Current Account Imbalances: Sustainability and Adjustment*, The University of Chicago.

Krasnikov, A., S. Jayachandran and V. Kumar (2009), The impact of customer relationship management implementation on cost and profit efficiencies: Evidence from the US commercial banking industry, *Journal of Marketing* 73, 61-76.

Kraus, A. and H.R. Stoll (1972a), Parallel trading by institutional investors, *Journal of Financial and Quantitative Analysis*, 7, 2107-38.

Kraus, A. and H.R. Stoll (1972b), Price impacts of block trading on the New York Stock Exchange, *Journal of Finance* 27(3), 569-588.

Kruglanski A.W., J.J. Bélanger, X. Chen, C. Köpetz, A. Pierro and L. Mannetti (2012), The energetics of motivated cognition: a force-field analysis, *Psychological Review* 119(1), 1-20.

Krugman, P. (2000), Thinking about the liquidity trap, *Journal of the Japanese and International Economies* 14(4), 221-237.

Kumar, A. and S. Lim (2008), How do decision frames influence the stock investment decisions of individual investors? *Management Science* 54, 1052–1064.

Kuran, T. and C. Sunstein (1999), Availability cascades and risk regulation, *Stanford Law Review* 51, 683–768.

Kuyper, H. and P. Dijkstra (2009), Better-than-average effects in secondary education: A 3-year follow-up, *Educational Research and Evaluation* 15(2), 167-184.

Kwan, V.S.Y., O.P. John, D.A. Kenny, M.H. Bond and R.W. Robins (2004), Reconceptualizing individual differences in self-enhancement bias: An interpersonal approach, *Psychological Review* 111(1), 94-110.

Kydland, F. and E.C. Prescott (1982), Time to build and aggregate fluctuations, *Econometrica* 50 (6), 1345-70.

Kyle, A.S. and F.A. Wang (1997), Speculation duopoly with agreement to disagree: Can overconfidence survive the market test? *Journal of Finance* 52, 2073–90.

La Porta, R.L., J. Lakonishok, A. Shleifer and R. Vishny (1997), Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52(2), 859-874.

Laffarga, J. and A. Mora (2002), La predición del fracaso empresarial: El estado de la cuestión en España, In F. Doldán and M. Rodríguez (eds.) *La Gestión del Riesgo de Crédito: Métodos y Modelos de Predición de la Insolvencia Empresarial*, AECA, 25-45.

Laffarga, J., J.Y. Martín and J. Vázquez (1985), El análisis de la solvencia en las instituciones bancarias: Propuesta de una metodología y aplicaciones a la banca española, *Esic-Market* 48, 51-83.

Lakonishok, J. and I. Lee (2001), Are insider tradings informative? *Review of Financial Studies* 14(1), 79-111.

Lakonishok, J. and S. Smidt (1986), Trading bargains in small firms at year-end, *The Journal of Portfolio Management* 12(3), 24-29.

Lakonishok, J. and S. Smidt (1988), Are seasonal anomalies real? A ninety year perspective, *Review of Financial Studies* 1(4), 403-425.

Lakonishok, J., A. Shleifer and R.W. Vishny (1992), The impact of institutional trading on stock prices, *Journal of Financial Economics* 32(1), 23-43.

Lakonishok, J., A. Shleifer and R.W. Vishny (1994), Contrarian investment, extrapolation, and risk, *The Journal of Finance* 49(5), 1541-78.

Lakonishok, J., A. Shleifer, R. Thaler and R. Vishny (1991), Window dressing by pension fund managers, *American Economic Review Papers and Proceedings* 81, 227-231.

Lamont, O.A. (2002), Macroeconomic forecasts and microeconomic forecasters, *Journal of Economic Behavior and Organization* 48, 265–80.

Lamont, O.A. and R.H. Thaler (2003), Anomalies: The law of one price in financial markets, *Journal of Economic Perspectives* 17(4), 191-202.

Lamoureux, C. and G. Zhou (1996), Temporary components of stock returns: what do the data tell us? *Review of Financial Studies* 9 (4), 1033-59.

Landman, J. and M. Manis (1983), Social cognition: Some historical and theoretical perspectives, *Advances in Experimental Social Psychology* 16, 49-123.

Lang, L. and R. Stulz (1994), Tobin's q, corporate diversification and firm performance, *Journal of Political Economy* 102, 1248-80.

Langer, E.J. (1975), The illusion of control, *The Journal of Personality and Social Psychology*, 32, 311-328, Reprinted short version in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Laplace, P.-S. (1774), Mémoires sur la probabilité des causes par les évènements, *Mémoires de l'Académie Royale des Sciences Paris* 6 (1774) pp. 621-656, repr. *Œuvres complètes*, vol. 8 (1891) p. 27-65, English by S.M. Stigler in: *Statistical Science* 1 (1986) pp. 359-378.

Larrick, R.P. (2004), Debiasing, In D.J. Koehler and N. Harvey (eds.), *Blackwell Handbook of Judgment and Decision Making*, Blackwell Publishing Ltd.

Lavoie, M. (1984), The endogenous flow of credit and the Post Keynesian Theory of Money, *Journal of Economic Issues* 18(3), 771-797.

Le Bon, G. (1896), *The Crowd: A Study of the Popular Mind*, T. Fisher Unwin.

Leary, M.T. and M.R. Roberts (2005), Do firms rebalance their capital structures? *The Journal of Finance* 60(6), 2575-2619.

Lee, C.M.C. and B. Swaminathan (2000), Price momentum and trading volume, *Journal of Finance* 55(5), 2017-69.

Lee, C.M.C., A. Shleifer and R.H. Thaler (1991), Investor sentiment and the closed-end fund puzzle, *The Journal of Finance* 46(1), 75-109.

Lehmann, B.N. (1990), Fads, martingales and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lei, V. and F. Vesely (2009), Market efficiency: Evidence from a no-bubble asset market experiment, *Pacific Economic Review* 14(2), 246-258.

Leiser, D., S. Bourgeois-Gironde and R. Benita (2010), Human foibles or systemic failure: Lay perceptions of the 2008-2009 financial crisis, *Journal of Socio-Economics* 39(2), 145-154.

Leland, H.E. and D.H. Pyle (1977), Informational asymmetries, financial structure and financial intermediation, *The Journal of Finance* 32, 371-387.

LeRoy, S.F. (1973), Risk aversion and the martingale property of stock prices, *International Economic Review* 14(2), 436-446.

LeRoy, S.F. and R.D. Porter (1981), The present-value relation: Tests based on implied variance bounds, *Econometrica* 49, 555-574.

LeRoy, S.F. and W.R. Parke (1992), Stock price volatility: Tests based on the geometric random walk, *American Economic Review* 82, 981-992.

Lev, B. (1978), *Análisis de los estados financieros: Un nuevo enfoque*, Esic, Madrid.

Levine, R. (2002), Bank-based or market-based financial systems: Which is better? *Journal of Financial Intermediation* 11, 398-428.

Levinson, J.D. and K. Peng (2007), Valuing cultural differences in Behavioral Economics, *The ICFAI Journal of Behavioral Finance* 4(1), 32-47.

Levitt, S.D. and J.A. List (2007), What do laboratory experiments measuring social preferences tell us about the real world? *Journal of Economic Perspectives* 21(2), 153-174.

Levitt, S.D. and J.A. List (2009), Field experiments in Economics: The past, the present, and the future, *European Economic Review* 53, 1-18.

Levy, R. (1967), Relative strength as a criterion for investment selection, *Journal of Finance* 22, 595-610.

Lewis, A. (2010), The credit crunch: Ideological, psychological and epistemological perspectives, *Journal of Socio-Economics* 39(2), 132-141.

Lichtenstein, S. and B. Fischhoff (1977), Do those who know more also know more about how much they know? *Organizational Behavior and Human Performance* 20, 159-183.

Lichtenstein, S., B. Fischhoff and L.D. Phillips (1982), Calibration of probabilities: The state of the art to 1980, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge U. Press.

Liebenstein, H. (1975), Aspects of the X-efficiency theory of the firm, *The Bell Journal of Economics* 6(2), 580-606.

Lintner, J.V. (1965), The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.

Lipsey, R.G. (1989), *An Introduction to Positive Economics*, Weidenfeld and Nicolson Ltd., 7th edition.

List, J.A. (2007), On the interpretation of giving in dictator games, *Journal of Political Economy* 115(3), 482-493.

List, J.A. (2009), An introduction to field experiments in economics, *Journal of Economic Behavior & Organization* 70, 439-442.

Liu, Y. and R. Taffler (2008), CEO overconfidence in M&A decision making and its impact on firm performance, *Technical report, working paper*, University of Edinburgh.

Liu, Y., S.H. Szewcyk and Z. Zantout (2008), Underreaction to dividend reductions and omissions? *Journal of Finance* 63(2), 987-1020.

Lo, A.W. (1997), *Market Efficiency: stock market behavior in theory and practice*, Edward Elgar Publishing Company.

Lo, A.W. (2004), The adaptive markets hypothesis, *Journal of Portfolio Management* 30, 15-29.

Lo, A.W. and A.C. MacKinlay (1988), Stock market prices do not follow random walks: evidence from a simple specification test, *Review of Financial Studies* 1(21), 41-66.

Lo, A.W. and A.C. MacKinlay (1990), When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-205.

Lo, A.W. and A.C. MacKinlay (2001), *A Non-Random Walk Down Wall Street*, Princeton University Press.

Lo, A.W., D.V. Repin and B.N. Steenbarger (2005), Fear and greed in financial markets: A clinical study of day-traders, *The American Economic Review* 95(2), 352-359.

Loewenstein, G. (1996), Out of control: Visceral influences on behavior, *Organizational Behavior and Human Decision Processes* 65(3), 272-292.

Loewenstein, G. (1999), Experimental economics from the vantage-point of behavioral economics, *The Economic Journal* 109, F25-F34.

Loewenstein, G., E.U. Weber, C.K. Hsee and N. Welch (2001), Risk as feelings, *Psychological Bulletin* 127(2), 267-86.

Loewenstein, G., T. O'Donoghue and M. Rabin (2003), Projection bias in predicting future utility, *Quarterly Journal of Economics* 118(4), 1209-48.

Lord, C.G., L. Ross and M.R. Lepper (1979), Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence, *Journal of Personality & Social Psychology* 37(11), 2098-2109.

Loughran, T. (1997), Book-to-market across firm size, exchange, and seasonality: Is there an effect? *Journal of Financial and Quantitative Analysis* 32(3), 249-268.

Loughran, T. and J.R. Ritter (1995), The new issues puzzle, *Journal of Finance* 50, 23-51.

Loughran, T. and J.R. Ritter (1996), Long-term market overreaction: The effect of low-priced stocks, *Journal of Finance* 51(5), 1959-70.

Loughran, T. and J.R. Ritter (2004), Why has IPO underpricing changed over time? *Financial Management* 33(3), 5-37.

Lovallo, D. and D. Kahneman (2003), Delusions of success: How optimism undermines executives' decisions, *Harvard Business Review* 81(7), 56-63.

Lozano-Vivas, A. and F. Pasiouras (2010), The impact of non-traditional activities on the estimation of bank efficiency: International evidence, *Journal of Banking & Finance* 34(7), 1436-49.

Lucas, R.E. (1972), Expectations and the Neutrality of Money, *Journal of Economic Theory* 4(2), 103–124.

Lucas, R.E. (1975), An equilibrium model of the business cycle, *Journal of Political Economy* 83 (6), 1113-144.

Lucas, R.E. (1978), Asset prices in an exchange economy, *Econometrica* 46 (6), 1429-1445.

Luenberger, D.G. (1992), Benefit function and duality, *Journal of Mathematical Economics* 21, 461-481.

Lundberg, E. (1937), *Studies in the theory of economic expansion*, London: p.s. King and Son, Ltd.

Lundeberg, M.A., P.W. Fox and J. Punccohar (1994), Highly confident but wrong: Gender differences and similarities in confidence judgments, *Journal of Educational Psychology* 86, 114-121.

Lunenburg, F.C. (2010), Group decision making: The potential for groupthink, *International Journal of Management, Business, and Administration* 13(1), 1-6.

Maenhout, P. (2004), Robust portfolio rules and asset pricing, *Review of Economic Studies* 17(4), 951-983.

Mahajan, J. (1992), The overconfidence effect in marketing management predictions, *Journal of Marketing Research* 29, 329-342.

Malkiel, B.G. (2003), *A Random Walk Down Wall Street*, N.Y.: W. W. Norton & Company, 8th edition.

Malmendier, U. and G. Tate (2005a), CEO overconfidence and corporate investment, *Journal of Finance* 60(6), 2661-2700.

Malmendier, U. and G. Tate (2005b), Does overconfidence affect corporate investment? CEO Overconfidence measures revisited, *European Financial Management* 11(5), 649-659.

Malmendier, U. and G. Tate (2008), Who makes acquisitions? CEO overconfidence and the market's reaction, *Journal of Financial Economics* 89, 20-43.

Malmendier, U., G. Tate and J. Yan (2011), Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies, *Journal of Finance* 66(5), 1687-1733.

Malmquist, S. (1953), Index numbers and indifference surfaces, *Trabajos de Estadísitca* 4, 209-242.

Mandelbrot, B. (1966), Forecasts of future prices, unbiased markets and martingale models, *Journal of Business* 39 (1), 242-255.

Mankiw, N.G. and S.P. Zeldes (1991), The consumption of stockholders and nonstockholders, *Journal of Financial Economics* 29(1), 97–112.

Manski, C. (2000), Economic analysis of social interactions, *Journal of Economic Perspectives* 14(3), 115-136.

Mansour, S.B., E. Jouini and C. Napp (2006), Is there a "pessimistic bias" in individual beliefs? Evidence from a simple survey, *Theory and Decision* 61(4), 345-362.

Marewski, J.N., W. Gaissmaier and G. Gigerenzer (2010), Good judgments do not require complex cognition, *Cognitive Processing* 11(2), 103-121.

Marín, J.M. and R. Rahi (2000), Information revelation and market incompleteness, *Review of Economic Studies* 67, 455-481.

Markowitz, H.M. (1952), Portfolio Selection, *The Journal of Finance* 7 (1), 77–91.

Markowitz, H.M. (1959), *Portfolio selection: Efficient diversification of investments*, John Wiley and Sons.

Marsh, T.A. and R.C. Merton (1986), Dividend variability and variance bounds tests for the rationality of stock market prices, *American Economic Review* 76 (3), 483-498.

Martikainen, T. and V. Puttonen (1996), Finnish day-of-the-week effects, *Journal of Business Finance and Accounting* 23, 1019–32.

Martin, A. and J. Ventura (2011a), Economic growth with bubbles, *American Economic Review* 102(6), 3033-58.

Martin, A. and J. Ventura (2011b), Theoretical notes on bubbles and the current crisis, *Working Paper Series* no. 1348, European Central Bank.

Mata, R. and L. Nunes (2010), When less is enough: Cognitive aging, information search, and decision quality in consumer choice, *Psychology and Aging* 25(2), 289-298.

McGraw, A.P., J.T. Larsen, D. Kahneman and D. Schkade (2010), Comparing gains and losses, *Psychological Science* 21(10), 1438-45.

McGuire, S.J. and D.M. Dilts (2008), The financial impact of standard stringency: An event study of successive generations of the ISO 9000 standard, *International Journal of Production Economics* 113(1), 3-22.

McQueen, G. (1992), Long-horizon mean-reverting stock prices revisited, *Journal of Financial and Quantitative Analysis* 27, 1 –18.

Meehl, P.E. (1954), *Clinical vs. statistical prediction: A theoretical analysis and a review of the evidence*, University of Minnesota Press.

Mehra, R. and E.C. Prescott (1985), The Equity premium: A puzzle, *Journal of Monetary Economics* 15, 145-61.

Mellers, B.A., A. Schwartz, K. Ho, & I. Ritov (1997), Decision affect theory: Emotional reactions to the outcomes of risky options, *Psychological Science* 8, 423-429.

Mendenhall, R.R. (2004), Arbitrage risk and post-earnings-announcement drift, *Journal of Business* 77(4), 875-894.

Mensi, S. and A. Zouari (2010), Efficient structure vs market power: Theories and empirical evidence, *International Journal of Economics and Finance* 2(4), 151-166.

Merkle, C. (2009), The disutility of the hard-easy effect in choice confidence, *Psychonomic Bulletin and Review* 16, 204-213.

Merkle, C. and M. Weber (2011), True overconfidence: The inability of rational information processing to account for apparent overconfidence, *Organizational Behavior and Human Decision Processes* 116(2), 262-271. Available at SSRN: http://ssrn.com/abstract=1373675

Mertens, J.F. and S. Zamir (1985), Formulation of bayesian analysis for games with incomplete information, *International Journal of Game Theory* 14, 1-29.

Merton, R. (1987), On the current state of the stock market rationality hypothesis, In R. Dornbusch, S. Fischer and I. Bossons (eds.), *Macroeconomics and Finance: Essays in Honor of Franco Modigliani*, MIT Press.

Merton, R.C. (1973a), Theory of rational option pricing, *Bell Journal of Economics and Management Science* 4 (1), 141–183.

Merton, R.C. (1973b), An intertemporal Capital Asset Pricing Model, *Econometrica* 41 (5), 867-887.

Merton, R.C. (1987a), On the current state of the stock market rationality hypothesis, In R. Dornbusch, S. Fischer and I. Bossons (eds.), *Macroeconomics and Finance: Essays in Honor of Franco Modigliani*, The MIT Press, Cambridge.

Merton, R.C. (1987b), A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42(3), 483-510.

Mester, L.J. (1996), A study of bank efficiency taking into account risk preferences, *Journal of Banking and Finance* 20, 1025-45.

Meulbroek, L. (2005), Company stock in pension plans: How costly is it? *Journal of law and Economics* 48, 443-474.

Michaely, R., R. Thaler and K. Womack (1995), Price reactions to dividend initiations and omissions, *Journal of Finance* 50(2), 573-608.

Michener, R.W. (1982), Variance bounds in a simple model of asset pricing, *Journal of Political Economy* 90, 166-175.

Milgram, S. (1963): Behavioral study of obedience, *The Journal of Abnormal and Social Psychology* 67(4), 371-378.

Milgram, S. (1974): *Obedience to authority; An experimental view*, Harpercollins.

Miller, J.G. (1984), Culture and the development of everyday social explanation, *Journal of Personality and Social Psychology* 46, 961-978.

Miller, M.H. (1986), Behavioral rationality in finance: The case of dividends, *Journal of Business* 59(4), S451–S468.

Miller, M.H. and F. Modigliani (1961), Dividend policy, growth and the valuation of shares, *Journal of Business* 34, 411-433.

Minsky, H.P. (1982a), The financial instability hypothesis: Capitalistic processes and the behavior of the economy, in C.P. Kindleberger and J.-P. Laffargue (eds.), *Financial Crises: Theory, History and Policy*, Cambridge: Cambridge University Press.

Minsky, H.P. (1982b), *Can "It" Happen Again? Essays on Instability and Finance*, M.E. Sharpe, Armonk, N.Y.

Minsky, H.P. (1992), The financial instability hypothesis, *The Jerome Levy Economics Institute*, Working Paper nº 74, available at www.levyinstitute.org/pubs/wp74.pdf

Mises, R. von (1928), *Probability, Statistics and Truth*, English ed., New York, Dover, 1981.

Mitchell, M., T. Pulvino, and E. Stafford (2002), Limited arbitrage in equity markets, *Journal of Finance* 57(2), 551-584.

Mitton, T. and K. Vorkink (2007), Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20(4), 1255-88.

Modigliani, F. and M.H. Miller (1958), The cost of capital, corporation finance and the theory of investment, *American Economic Review* 48 (3), 261–297.

Modigliani, F. and M.H. Miller (1959), The cost of capital, corporation finance and the theory of investment: Reply, *American Economic Review* 49, 655-669.

Modigliani, F. and R. Brumberg (1954), Utility analysis and the consumption function: An interpretation of cross-section data, in K. Kurihara (ed.), *Post Keynesian Economics* (Rutgers University Press, New Brunswick, NJ).

Moore, B.J. (1988), The endogenous money supply, *Journal of Post Keynesian Economics* 10(3), 372-385.

Moore, D.A. and D.A. Small (2007), Error and bias in comparative social judgment: On being both better and worse than we think we are, *Journal of Personality and Social Psychology* 92(6), 972-989.

Moore, D.A. and D.A. Small (2008), When it's rational for the majority to believe that they are better than average, In J.I. Krueger (Ed.), *Rationality and social responsibility: Essays in honor of Robyn M. Dawes*, Mahwah, NJ: Erlbaum.

Moore, D.A. and D.M. Cain (2007), Overconfidence and underconfidence: When and why people underestimate (and overestimate) the competition, *Organizational Behavior and Human Decision Processes* 103, 197-213.

Moore, D.A. and P.J. Healy (2008), The trouble with overconfidence, *Psychological Review* 115(2), 502–517.

Moore, P.G. (1977), The manager's struggle with uncertainty, *Journal of The Royal Statistical Society Series A* 149, 129-165.

Mora, A. (1994), Los modelos de predición del fracaso empresarial: Una aplicación empírica del Logit, *Revista Española de Financiación y Contabilidad* 78, 203-233.

Morris, S. (1995), The common prior assumption in economic theory, *Economics and Philosophy* 11, 227-253.

Mullainathan, S. and R.H. Thaler (2000), Behavioral Economics, *MIT Dept. of Economics Working Paper No. 00-27*, available at SSRN: http://ssrn.com/abstract=245828

Muth, J.F. (1961), Rational expectations and the theory of price movements, *Econometrica* 29 (3), 315-335.

Nadeau, R., E. Cloutier and J.-H.Guay (1993), New evidence about the existence of a bandwagon effect in the opinion formation process, *International Political Science Review* 14(2), 203–213.

Narayan, P.K. (2006), The behavior of U.S. stock prices: Evidence from a threshold autoregressive model, *Mathematics and Computers in Simulation* 71(2), 103-108.

Neely, C.J. and P.A. Weller (1999), Technical trading rules in the European Monetary System, *Journal of International Money and Finance* 18(3), 429-458.

Neilson, W.S. (2002), Comparative risk sensitivity with reference-dependent preferences, *Journal of Risk and Uncertainty* 24, 131-142.

Nijman, T., L. Swinkels and M. Verbeek (2004), Do countries or industries explain momentum in Europe? *Journal of Empirical Finance* 11(4), 461-481.

Nisbett, R.E. and T. Masuda (2003), Culture and point of view, *Proceedings of the National Academy of Science* 100, 11163-70.

Nisbett, R.E. and T.D. Wilson (1977), The halo effect: Evidence for unconscious alteration of judgments, *Journal of Personality and Social Psychology* 35(4), 250–256.

Nisbett, R.E., D.H. Krantz, C. Jepson and G.T. Fong (1982), Improving inductive inference, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Nisbett, R.E., E. Borgida, R. Crandall and H. Reed (1976), Popular induction: Information is not necessarily informative, Reprinted short version in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Niu, J. (2010), The effect of CEO overconfidence on bank risk taking, *Economics Bulletin* 30(4), 3288-99.

Nobel Prize (2013), The Prize in Economic Sciences 2013 - Advanced Information, *Nobelprize.org*, Nobel Media AB 2013. Available from http://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2013/advanced.html

Nofsinger, J.R. and R.W. Sias (1999), Herding and feedback trading by institutional and individual investors, *The Journal of Finance* 54(6), 2263-95

Nourayi, M.M. (1994), Stock price responses to the SEC's enforcement actions, *Journal of Accounting and Public Policy* 13(4), 333-347.

Novemsky, N. and D. Kahneman (2005), The boundaries of loss aversion, *Journal of Marketing Research* 42(2), 119-128.

Novshek, W. and H. Sonnenschein (1987), General equilibrium with free entry: A synthetic approach to the theory of perfect competition, *Journal of Economic Literature* 25(3), 1281-1306.

Odean, T. (1998a), Are investors reluctant to realize their losses? *Journal of Finance* 53(5), 1775-98.

Odean, T. (1998b), Volume, volatility, price and profit when all traders are above average, *Journal of Finance* 53(6), 1887-1934.

Odean, T. (1999), Do investors trade too much? *The American Economic Review* 89(5), 1279-98.

Officer, R. (1975), Seasonality in the Australian capital markets: Market efficiency and empirical issues, *Journal of Financial Economics* 2, 29-51.

Okun, A. (1981), *Prices and quantities: A macro-economic analysis*, The Brookings Institution.

Oppenheimer, D.M., R.A. Leboeuf, and N.T. Brewer (2008), Anchors aweigh: A demonstration of cross-modality anchoring and magnitude priming, *Cognition* 106, 13-26.

Ortmann, A., G. Gigerenzer, B. Borges and D.G. Goldstein (2008), The recognition heuristic: A fast and frugal way to investment choice? In C.R. Plott and V.L. Smith (eds.) *Handbook of experimental economics results: vol 1*, Handbooks in Economics 28, 993–1003.

Osborne, M.F.M. (1959), Brownian motions in the stock market, *Operations Research* 7(2), 145-173.

Osborne, M.F.M. (1962), Periodic structure in the Brownian motion of stock prices, *Operations Research* 10(3), 345-379.

Oskamp, S. (1965), Overconfidence in case-study judgments, *The Journal of Consulting Psychology* 29, 261-265. Reprinted in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Otrok, C., B. Ravikumar and C.H. Whiteman (2007), A generalized volatility bound for dynamic economies, *Journal of Monetary Economics* 54(8), 2269-90.

Ottaviani, M. and P. Sorensen (2007), The favorite-longshot bias: An overview of the main explanations, in D. Hausch and W. Ziemba (eds.) *Efficiency of Sports and Betting Markets*, Elsevier: Handbook in Finance Series.

Pan, C. and M. Statman (2010), Beyond risk tolerance: regret, overconfidence and other investor propensities, *SCU Leavey School of Business*, Research Paper No. 10-05.

Parejo, J.A., L. Rodríguez, A. Calvo and A. Cuervo (2011), *Manual del Sistema Financiero Español*, Madrid: Ariel, Economía y Empresa, 23ª Edición.

Park, S.H. and K. Dongcheoi (1997), Market valuation of joint ventures: Joint venture characteristics and wealth gains, *Journal of Business Venturing* 12(2), 83-108.

Pätäri, E.J. (2009), Do hot hands warm the mutual fund investor? The myth of performance persistence phenomenon, *International Research Journal of Finance and Economics* 34, 117-139.

Patel, J.M. (1989), Discussion on the usefulness of earnings research: Lessons and directions from two decades of empirical research, *Journal of Accounting Research* 27, 193-201.

Patro, D.K. and Y. Wu (2004), Predictability of short-horizon returns in international equity markets, *Journal of Empirical Finance* 11(4), 553-584.

Pearlman, J.G. and T.J. Sargent (2005), Knowing the Forecasts of Others, *Review of Economic Dynamics* 8(2), 480-497.

Peirce, C.S. (1910), Notes on the doctrine of chances, In Hartshorne, C. and P. Weiss (eds.), *Collected Papers of Charles Sanders Peirce* vol. 2 (1931), 405-14.

Penman, S.H., S.A. Richardson and I. Tuna (2007), The book-to-price effect in stock returns: Accounting for leverage, *Journal of Accounting Research* 45(2), 427-467.

Peón, D. and A. Calvo (2010), Using behavioral economics to analyze credit policies on the banking industry, *4th International Conference on Applied Business & Economics (ICABE)*, A Coruña, September 2010, available at SSRN: http://ssrn.com/abstract=1831346

Peón, D. and A. Calvo (2012a), Using behavioral economics to analyze credit policies in the banking industry, *European Research Studies* 15(3), 135-144.

Peón, D. and A. Calvo (2012b), A behavioral analysis of informational efficiency in bank-based financial systems, *19th Annual Conference of the Multinational Finance Society*, Krakow, June 2012.

Peón, D., A. Calvo and M. Antelo (2014), A short test for overconfidence and prospect theory: An experimental validation, *MPRA working paper 57899*, Munich Personal RePEc Archive, available at http://mpra.ub.uni-muenchen.de/57899/

Peón, D., M. Antelo and A. Calvo (2015), On informational efficiency of the banking sector: A behavioral model of the credit boom, *Studies in Economics and Finance* 32(2), forthcoming.

Peters, E.E. (1991), *Chaos and Order in the Capital Markets*, John Wiley & Sons, New York.

Petty, R.E. and P. Briñol (2008), Persuasion: From single to multiple to metacognitive processes, *Perspectives on Psychological Science* 3(2), 137-147.

Peyer, U. and T. Vermaelen (2009), The nature and persistence of buyback anomalies, *Review of Financial Studies* 22(4), 1693-1745.

Phelps, E.S. and Pollak, R.A. (1968), On second-best national saving and game-equilibrium growth, *Review of Economic Studies* 35(2), 185-199.

Plott, C.R. and V.L. Smith (2008), *Handbook of Experimental Economics Results*, Elsevier.

Plous, S. (1991), Biases in the assimilation of technological breakdowns: Do accidents make us safer? *Journal of Applied Social Psychology* 221(13), 1058-82.

Plous, S. (1993), *The Psychology of Judgment and Decision Making*, McGraw-Hill.

Polkovnichenko, V. (2005), Household portfolio diversification: A case for rank-dependent preferences, *Review of Financial Studies* 18, 1467-1502.

Pontiff, J. (1996), Costly arbitrage: Evidence from closed-end funds, *The Quarterly Journal of Economics* 111(4), 1135-51.

Pontiff, J. and J. Schall (1998), Book-to-market ratios as predictors of market returns: Evidence and implications, *Journal of Financial Economics*, 22, 27-59.

Popper, K.R. (1959), *The Logic of Scientific Discovery*, New York, Basic Books.

Por, H.-H. and D.V. Budescu (2013), Revisiting the gain–loss separability assumption in prospect theory, *Journal of Behavioral Decision Making* 26, 385–396.

Porras, D. and M. Griswold (2000), The Value Line enigma revisited, *Quarterly Journal of Business and Economics* 39(4), 39-50.

Porter, D.P. and V.L. Smith (1995), Futures contracting and dividend uncertainty in experimental asset markets, *Journal of Business* 68(4), 509–541.

Poterba, J.M. and L.H. Summers (1988), Mean reversion in stock prices: Evidence and implications, *Journal of Financial Economics* 22(1), 27-59.

Pratt, J.W. (1964), Risk aversion in the small and in the large, *Econometrica* 32(1/2), 122-136.

Prelec, D. (1998), The probability weighting function, *Econometrica* 66(3), 497-527.

Prendergast, C. and L. Stole (1996), Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning, *Journal of Political Economy* 104, 1105–34.

Presbitero, A.F., G.F. Udell and A. Zazzaro (2012a), The home bias and the credit crunch: A regional perspective, *MoFiR workshop on banking*, http://www.voxeu.org/index.php?q=node/7614

Presbitero, A.F., G.F. Udell and A. Zazzaro (2012b), Home bias and the credit crunch: Evidence from Italy, *voxEu.org*, available at http://www.voxeu.org/index.php?q=node/7614

Presson, P.K. and V.A. Benassi (1996), Illusion of control: A meta-analytic review, *Journal of Social Behavior and Personality* 11, 493-510.

Prince, M. (1993), Women, men, and money stiles, *Journal of Economic Psychology* 14, 175-182.

Pronin, E. and M.B. Kugler (2007), Valuing thoughts, ignoring behavior: The introspection illusion as a source of the bias blind spot, *Journal of Experimental Social Psychology* 43(4), 565–578.

Purnanandam, A.K. and B. Swaminathan (2004), Are IPOs really underpriced? *Review of Financial Studies* 17(3), 811-848.

Rabin, M. (1998), Psychology and Economics, *Journal of Economic Literature* 36(1), 11-46.

Rabin, M. (2000), Risk aversion and expected-utility theory: A calibration theorem, *Econometrica* 68(5), 1281-92.

Rabin, M. (2002a), A perspective on Psychology and Economics, *European Economic Review* 46(4-5), 657-685.

Rabin, M. (2002b), Inference by believers in the Law of Small Numbers, *Quarterly Journal of Economics* 117, 775-816.

Rabin, M. and D. Vayanos (2010), The gambler's and hot-hand fallacies: Theory and applications, *Review of Economic Studies* 77(2), 730-778.

Rabin, M. and J. Schrag (1999), First impressions matter: A model of confirmatory bias, *Quarterly Journal of Economics* 114(1), 37-82.

Rabin, M. and R.H. Thaler (2001), Anomalies: Risk aversion, *The Journal of Economic Perspectives* 15(1), 219-232.

Radner, R. (1968), Competitive equilibrium under uncertainty, *Econometrica* 36, 31-58.

Radner, R. (1979), Rational expectations equilibrium: Generic existence and the information revealed by prices, *Econometrica* 47 (3), 655-678.

Raghavendra Rau, P. and T. Vermaelen (1998), Glamour, value and the post-acquisition performance of acquiring firms, *Journal of Financial Economics* 49(2), 223-253.

Raghubir, P. and J. Srivastava (2009), The denomination effect, *Journal of Consumer Research* 36(4), 701-713.

Raghubir, P. and S. Ranjan Das (1999), A case for theory-driven experimental enquiry, *Financial Analysts Journal* 55(6), 56-79.

Ramsey, F.P. (1926), Truth and Probability, in Ramsey, 1931, *The Foundations of Mathematics and other Logical Essays*, Ch. VII, p.156-198, edited by R.B. Braithwaite, London: Kegan, Paul, Trench, Trubner & Co., New York: Harcourt, Brace and Company.

Read, D., G. Loewenstein and M. Rabin (1999), Choice bracketing, *Journal of Risk and Uncertainty* 19, 171-197.

Reichenbach, H. (1949a), *The Theory of Probability. An Inquiry into the Logical and Mathematical Foundation of the Calculus of Probability*, Berkeley/LA: University of California Press.

Reichenbach, H. (1949b), The philosophical significance of the theory of relativity, in P.A. Schilpp (ed.), *Albert Einstein: Philosopher-scientist*, Evanston: The Library of Living Philosophers, pp. 287-311.

Reinganum, M.R. (1981), Misspecification of capital asset pricing: Empirical anomalies based on earnings yields and market values, *Journal of Financial Economics* 12, 89-104.

Reinganum, M.R. (1982), A direct test of Roll's conjecture on the firm size effect, *Journal of Finance* 37, 27-36.

Reinhart, C.M. and K.S. Rogoff (2011), From financial crash to debt crisis, *American Economic Review*, 101(5), 1676-1706.

Rhodes-Kropf, M., D.T. Robinson and S. Viswanathan (2005), Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561–603.

Ricci, U. (1930), Die synthetische ökonomie von Henry Ludwell Moore, *Zeitschrift für Nationalökonomie* I.

Ricciardi, V. and H.K. Simon (2000), What is Behavioral Finance? *Business, Education & Technology Journal* 2(2), 1-9.

Richardson, S., S.H. Teoh and P.D. Wysocki (2004), The walk-down to beatable analyst forecasts: The role of equity issuance and insider trading incentives, *Contemporary accounting research* 21, 885-924.

Richins, M.L. (1991), Comparison and the idealized images of advertising, *Journal of Consumer Research* 18(1), 71-83.

Rieger, M.O. and M. Wang (2008a), Prospect theory for continuous distributions, *Journal of Risk and Uncertainty* 36, 83–102.

Rieger, M.O. and M. Wang (2008b), What is behind the priority heuristic: A mathematical analysis and comment on Brandstätter, Gigerenzer, and Hertwig (2006), *Psychological Review* 115, 274–280.

Rigobon, R. and B. Sack (2004), The impact of monetary policy on asset prices, *Journal of Monetary Economics* 51(8), 1553-75.

Ritov, I. and J. Baron (1990), Reluctance to vaccinate: omission bias and ambiguity, *Journal of Behavioral Decision Making* 3, 263-277.

Ritter, J.R. (1991), The long-run performance of initial public offerings, *Journal of Finance* 46(1), 3-27.

Ritter, J.R. and I. Welch (2002), A review of IPO activity, pricing, and allocations, *Journal of Finance* 57(4), 1795-1828.

Robbins L. (1935), *An Essay on the Nature and Significance of Economic Science*, London: MacMillan and Co.

Roberts, H. (1967), Statistical vs. clinical prediction of the stock market, *unpublished manuscript*, Seminar on the Analysis of Security Prices, University of Chicago; cit. Brealey and Myers (1981), *Principles of Corporate Finance*, McGraw-Hill, p. 262.

Roca, M., R.M. Hogarth and J. Maule (2006), Ambiguity seeking as a result of the status quo bias, *Journal of Risk and Uncertainty* 32(3), 175-194.

Rodrigues, A.F., N. Da Costa and S. Da Silva (2011), Overconfidence and excess entry: A comparison between students and managers, *Economics Bulletin* 31(3), 2549-57.

Rodríguez, M. (2000), Métodos y modelos de pronóstico del fracaso empresarial: Una aproximación empírica a la realidad empresarial de la CC.AA de Galicia, *Doctoral thesis*, University of A Coruna.

Rodríguez, M. (2002), Modelos de insolvencia en empresas gallegas: Aplicación de técnicas paramétricas y de inteligencia artificial, In F. Doldán and M. Rodríguez (eds.) *La Gestión del Riesgo de Crédito: Métodos y Modelos de Predición de la Insolvencia Empresarial*, AECA, 73-114.

Roediger, H.L. and K.B. McDermott (1995), Creating false memories: Remembering words not presented in lists, *Journal of Experimental Psychology: Learning, Memory, and Cognition* 21, 803-814.

Roll, R. (1981), A possible explanation of the small firm effect, *The Journal of Finance* 36(4), 879-888.

Roll, R. (1984), Orange juice and weather, *The American Economic Review* 74 (5), 861-880.

Roll, R. (1986), The hubris hypothesis of corporate takeovers, *Journal of Business* 59(2), 197-216.

Rosenberg, B., K. Reid, and R. Lanstein (1985), Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9-17.

Rosenthal, L. and C. Young (1990), The seemingly anomalous price behavior of Royal Dutch/Shell and Unilever N.V./PLC, *Journal of Financial Economics* 26(1), 123-141.

Ross, D. (2008), Two styles of neuroeconomics, *Economics and Philosophy* 24(3), 473-483.

Ross, L. (1977), The false consensus effect: An egocentric bias in social perception and attribution processes, *Journal of Experimental Social Psychology* 13(3), 279–301.

Ross, L. and C.A. Anderson (1982), Shortcomings in the attribution process: On the origins and maintenance of erroneous social assessments, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Ross, M. and F. Sicoly (1977), Egocentric biases in availability and attribution, Reprinted short version in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Ross, S. (1976), The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13 (3), 341–360.

Rötheli, T.F. (2012a), Oligopolistic banks, bounded rationality, and the credit cycle, *Economics Research International*, Vol. 2012, Article ID 961316, 4 pages, 2012. doi:10.1155/2012/961316.

Rötheli, T.F. (2012b), Boundedly rational banks' contribution to the credit cycle, *The Journal of Socio-Economics* 41, 730-737.

Rothschild, M. and J.E. Stiglitz (1976), Equilibrium in competitive insurance markets: An essay on the economics of imperfect information, *The Quarterly Journal of Economics* 90(4), 629-649.

Rouwenhorst, G. (1998), International momentum strategies, *Journal of Finance* 53, 267-284.

Rozeff, M. and W. Kinney (1976), Capital market seasonality: The case of stock returns, *Journal of Financial Economics* 3, 379-402.

Rozin, P. and C. Nemeroff (2002), Sympathetic magical thinking: the contagion and similarity "heuristics", In T. Gilovich, D. Griffin and D. Kahneman (eds.), *Heuristics and biases. The psychology of intuitive judgment*, (pp. 201-216), Cambridge: Cambridge University Press.

Ruiz, V. (2005), La hipótesis débil del mercado eficiente: Análisis intradiario de los osciladores e indicadores técnicos en el Mercado bursátil español, *Doctoral thesis*, Euskal Herriko Unibertsitatea.

Sadka, R. (2005), Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80(2), 309-349.

Salovey, P. and J. Rodin (1984), Some antecedents and consequences of social-comparison jealousy, Journal of Personality and Social Psychology, 47(4), 780-792.

Samuelson, P.A. (1948), Dynamic process analysis, in Ellis, H.S. (ed.), *A Survey of Contemporary Economics*, The American Economic Association, 352-87.

Samuelson, P.A. (1958), An exact consumption-loan model of interest with or without the social contrivance of money, *Journal of Political Economy* 66, 467-482.

Samuelson, P.A. (1963), Risk and uncertainty: A fallacy of large numbers, *Scientia* 98, 108-113.

Samuelson, P.A. (1965), Proof that properly anticipated prices fluctuate randomly, *Industrial Management Review* 6, 41-49.

Samuelson, P.A. (1998), Summing upon business cycles: Opening address, in J.C. Fuhrer and S. Schuh (eds.) *Beyond Shocks: What Causes Business Cycles*, Boston: Federal Reserve Bank of Boston, 33-36.

Samuelson, W. and R. Zeckhauser (1988), Status quo bias in decision making, *Journal of Risk and Uncertainty* 1(1), 7-59.

Sandroni, A. and F. Squintani (2007), Overconfidence, insurance, and paternalism, *The American Economic Review* 97(5), 1994-2004

Sandroni, A. and F. Squintani (2009), Overconfidence and asymmetric information in insurance markets, *working paper*, available at www.imtlucca.it/whats_new/_seminars_docs/000174-paper_Squintani_April6.pdf

Sanna, L.J. and N. Schwarz (2003), Debiasing the hindsight bias: The role of accessibility experiences and (mis)attributions, *Journal of Experimental Social Psychology* 39, 287–295.

Sargent, T. and N. Wallace (1975), 'Rational' expectations, the optimal monetary instrument, and the optimal money supply rule, *Journal of Political Economy* 83 (2), 241-54.

Sauer, D.A. (1997), Information content of prior mutual fund performance rankings, *Journal of Economics and Business* 49(6), 549-567.

Savage, L.J. (1954), *The Foundations of Statistics*, New York: Wiley

Scharfstein, D. and J. Stein (1990), Herd behavior and investment, *American Economic Review* 80, 469-475.

Scheinkman, J.A. and W. Xiong (2003). Overconfidence and speculative bubbles, *Journal of Political Economy* 111(6), 1183-1219.

Scherbina, A. (2013), Asset price bubbles: A selective survey, *IMF Working Paper* WP/13/45, available at http://www.imf.org/external/pubs/ft/wp/2013/wp1345.pdf

Schmeling, M. (2009), Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16(3), 394-408.

Schmidt, U. and S. Traub (2002), An experimental test of loss aversion, *Journal of Risk and Uncertainty* 25, 233-249.

Schmidt, U., C. Starmer and R. Sugden (2008), Third generation prospect theory, *Journal of Risk and Uncertainty* 36(3), 203-223.

Schneider, E. (1948), *Einführung in die Wirtschaftstheorie*, J.C.B. Mohr, Tübingen.

Scholes, M.S. (1972), The market for securities: Substitution versus price pressure and the effects of information on share prices, *Journal of Business* 45(2), 179-211.

Schooler, L.J. and R. Hertwig (2005), How forgetting aids heuristic inference, *Psychological Review* 112, 610-628.

Schultz, H. (1930), *Der Sinn der statischtischen Nachfragekurven*, Veröffentlichen der Frankfurter Gesellschaft für Konjunkturforschung, heft 10, Bonn.

Selden, G.C. (1912), *Psychology of the Stock Market: Human Impulses Lead To Speculative Disasters*, Ticker Publishing.

Sen, A. (1995), Moral codes and economic success, In C.S. Brittan and A. Hamlin (eds.) *Market Capitalism and Moral Values*, Brookfield, Aldershot.

Seyhun, H.N. (1988), The information content of aggregate insider trading, *Journal of Business* 61(1), 1-24.

Shafir, E. and A. Tversky (1992). Thinking through uncertainty: Non-consequential reasoning and choice, *Cognitive Psychology* 24, 449–474.

Shafir, E. and R.H. Thaler (2006), Invest now, drink later, spend never: The mental accounting of delayed consumption, *Journal of Economic Psychology* 27, 694-712.

Shane, P.B. and T. Stock (2006), Security analyst and stock market efficiency in anticipating tax-motivated income shifting, *Accounting Review* 81(1), 227-250.

Sharpe, W.F. (1963), A simplified model for portfolio analysis, *Management Science* 9, 277-293.

Sharpe, W.F. (1964), Capital asset prices – A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

Sharpe, W.F. (1966), Mutual fund performance, *Journal of Business* 39(1), 119-138.

Sharpe, W.F. (1981), Decentralized investment management, *Journal of Finance* 36(2), 217-234.

Sharpe, W.F. and G.J. Alexander (1990), *Investments*, 4th edition, Prentice Hall.

Shefrin, H. (1999), Irrational exuberance and option smiles, *Financial Analysts Journal* 55(6), 91-103.

Shefrin, H. (2000), *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*, Oxford University Press, second edition (2002).

Shefrin, H. (2001a), *Behavioral Finance*, Edward Elgar.

Shefrin, H. (2001b), On kernels and sentiment, *working paper*, Santa Clara University, available at SSRN: http://ssrn.com/abstract=288258

Shefrin, H. (2001c), Behavioral corporate finance, *Journal of Applied Corporate Finance* 14, 113–124.

Shefrin, H. (2006), *Behavioral Corporate Finance*, McGraw-Hill.

Shefrin, H. (2008a), *A Behavioral Approach to Asset Pricing*, Elsevier, 2nd edition.

Shefrin, H. (2008b), *Ending the Management Illusion: How to Drive Business Results Using the Principles of Behavioral Finance*, Mc-Graw Hill, 1st edition.

Shefrin, H. and E.M. Cervellati (2011), BP's failure to debias: Underscoring the importance of behavioral corporate finance, *Quarterly Journal of Finance* 1(1), 127-168.

Shefrin, H. and M. Statman (1984), Explaining investor preference for cash dividends, *Journal of Financial Economics* 13(2), 253-82.

Shefrin, H. and M. Statman (1985), The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777-790.

Shefrin, H. and M. Statman (1994), Behavioral Capital Asset Pricing Theory, *Journal of Financial and Quantitative Analysis* 29(3), 323-349.

Shefrin, H. and M. Statman (2000), Behavioral portfolio theory, *Journal of Financial and Quantitative Analysis* 35(2), 127-151.

Shepherd, W.G. (1986), Tobin's q and the structure-performance relationship: comment, *The American Economic Review* 76(5), 1205-10.

Sherif, M. (1937), An experimental approach to the study of attitudes, *Sociometry* 1, 90-98.

Shiller, R.J. (1979), The volatility of long-term interest rates and expectations models of the Term Structure, *Journal of Political Economy* 87, 1190-1219.

Shiller, R.J. (1981), Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* 71(3), 421-436.

Shiller, R.J. (1984), Stock prices and social dynamics, *Brookings Papers on Economic Activity*, Fall: 457-498.

Shiller, R.J. (1995), Speculative behavior and the functioning of risk markets, *Moneda y Crédito* 200, 11-52.

Shiller, R.J. (2000a), Human behavior and the efficiency of the financial system, In B. Taylor and M. Woodfood (eds.), *Handbook of Macroeconomics*, Amsterdam: North Holland.

Shiller, R.J. (2000b), *Irrational exuberance*, Princeton University Press.

Shiller, R.J. (2002), Bubbles, human judgment, and expert opinion, *Financial Analysts Journal* 58(3), 18-26.

Shiller, R.J. (2003), From efficient markets theory to behavioral finance, *Journal of Economic Perspectives* 17(1), 83-104.

Shiller, R.J. (2005), Behavioral economics and institutional innovation, *Southern Economic Journal* 72(2), 269-283.

Shiller, R.J. and P. Perron (1985), Testing the random walk hypothesis: Power vs. frequency of observation, *Economics Letters* 18, 381-386.

Shiller, R.J., J.Y. Campbell, and K.L. Schoenholtz (1983), Forward rates and future policy: interpreting the term structure of interest rates, *Brookings Papers on Economic Activity* 1, 173-223.

Shin, H.S. (1992), Prices of state contingent claims with insider traders, and the favorite-longshot bias, *The Economic Journal* 102(411), 426-435.

Shivakumar, L. (2000), Do firms mislead investors by overstating earnings before seasoned equity offerings, *Journal of Accounting and Economics* 29(3), 339-371.

Shively, P.A. (2003), The nonlinear dynamics of stock prices, *Quarterly Review of Economics and Finance* 43(3), 505-517.

Shleifer, A. (1986), Do demand curves for stocks slope down, *Journal of Finance* 41(3), 579-590.

Shleifer, A. (2000), *Inefficient Markets: An Introduction to Behavioral Finance*, Oxford University Press.

Shleifer, A. (2004), Does competition destroy ethical behavior? *American Economic Association Papers and Proceedings* 94(2), 414-418.

Shleifer, A. and R.W. Vishny (1997), The limits of arbitrage, *Journal of Finance* 52(1), 35–55.

Shleifer, A. and R.W. Vishny (2003), Stock market driven acquisitions, *Journal of Financial Economics* 70, 295-311.

Siegel, J. (1998), *Stocks for the Long Run*, McGraw Hill.

Simar, L. and P. Wilson (2007), Estimation and inference in two-stage, semi-parametric models of productions processes, *Journal of Econometrics* 136, 31-64.

Simkowitz, M. and W. Beedles (1978), Diversification in a three-moment world, *Journal of Financial and Quantitative Analysis* 13, 927-941.

Simon, H.A. (1955), A behavioral model of rational choice, *Quarterly Journal of Economics* 69(1), 99-118.

Simon, H.A. (1957), *Models of Man: Social and Rational*, Wiley.

Simon, H.A. (1959), Theories of decision-making in Economics and Behavioral Science, *American Economic Review* 49(3), 253-283.

Simonson, I. and A. Tversky (1992), Choice in context: Tradeoff contrast and extremeness aversion, *Journal of Marketing Research* 29(3), 281-295.

Singer, M. (1971), The vitality of mythical numbers, *The Public Interest* 23, 3-9.

Slovic, P. (1972), Psychological Study of Human Judgment: Implications for Investment Decision Making, *Journal of Finance* 27(4), 779-799.

Slovic, P. and S. Lichtenstein (1971), Comparison of Bayesian and regression approaches to the study of information processing in judgment, *Organizational Behavior & Human Performance* 6(6), 649-744.

Slovic, P., M.L. Finucane, E. Peters and D.G. MacGregor (2002), The affect heuristic, In T. Gilovich, D. Griffin and D. Kahneman, eds., *Heuristics and Biases: The Psychology of Intuitive Judgment*, Cambridge University Press, 397-420.

Smirlok, M. (1985), Evidence on the (non) relationship between concentration and profitability in banking, *Journal of Money, Credit and Banking* 17(1), 69-83.

Smith, A. (1759), *The Theory of Moral Sentiments*, 1892, Prometheus.

Smith, V.L. (2001), Experimental economics, *International Encyclopedia of the Social & Behavioral Sciences*, 5100-08.

Smith, V.L., G.L. Suchanek and A.W. Williams (1988), Bubbles, crashes, and endogenous expectations in experimental spot asset markets, *Econometrica* 56(5), 1119-51.

Soll, J.B. (1996), Determinants of overconfidence and miscalibration: The roles of random error and ecological structure, *Organizational Behavior and Human Decision Processes* 65(2), 117-137.

Soll, J.B. and J. Klayman (2004), Overconfidence in interval estimates, *Journal of Experimental Psychology: Learning, Memory and Cognition* 30(2), 299-314.

Solow, R. (1980), On theories of unemployment, *American Economic Review* 70, 1-11.

Soros, G. (2010), *Mi Filosofía*, Taurus.

Soufian, M., W. Forbes and R. Hudson (2012), Adapting financial rationality: Is a new paradigm emerging? *19th Annual Conference of the Multinational Finance Society*, Krakow, June 2012.

Spiess, D.K. and J. Affleck-Graves (1995), Underperformance in long-run stock returns following seasoned equity offerings, *Journal of Financial Economics* 38, 243-267.

Stankov, L., G. Pallier, V. Danthiir and S. Morony (2012), Perceptual underconfidence: A conceptual illusion? *European Journal of Psychological Assessment* 28(3), 190-200.

Starks, L.T., L. Yong and L. Zheng (2006), Tax-loss selling and the January effect: Evidence from municipal bond closed-end funds, *Journal of Finance* 61(6), 3049-3067.

Starmer, C. (2000), Developments in non-expected utility theory: The hunt for a descriptive theory of choice under risk, *Journal of Economic Literature* 38(2), 332-382.

Statman, M. (1987), How many stocks make a diversified portfolio? *Journal of Financial and Quantitative Analysis* 22, 353-363.

Statman, M. (1995), Behavioral Finance versus Standard Finance, In A. S. Wood (ed.), *Behavioral Finance and Decision Theory in Investment Management*, Charlottesville, VA: AIMR.

Statman, M. (1999), Behavioral finance: Past battles, future engagements, *Financial Analysts Journal* 55(6), 18-27.

Statman, M. and J.A. Weng (2010), Investment across cultures: Financial Attitudes of Chinese-Americans, *Journal of Investment Consulting* 11(1), 37-44.

Statman, M., S. Thorley and K. Vorkink (2006), Investor overconfidence and trading volume, *The Review of Financial Studies* 19(4), 1531-65.

Stattman, D. (1980), Book values and stock returns, *The Chicago MBA: A Journal of Selected Papers* 4, 25-45.

Stein, J.C. (1996), Rational capital budgeting in an irrational world, *The Journal of Business* 69(4), 429-455.

Stigler, A. (1964), A theory of oligopoly, *Journal of Political Economy* 72, 44-61.

Stiglitz, J.E. (1982), The inefficiency of the stock market equilibrium, *Review of Economic Studies* 69, 241-261.

Stiglitz, J.E. (1991), The invisible hand and modern welfare economics, *working paper NBER w3641*, available from SSRN: http://ssrn.com/abstract=227430.

Stiglitz, J.E. (1993), The role of the state in financial markets, *World Bank Research Observer, Annual Conference on Development Economics Supplement* (1993), 19-61.

Stiglitz, J.E. (2012), *The Price of Inequality: How Today's Divided Society Endangers our Future*, Norton.

Stiglitz, J.E. and A. Weiss (1981), Credit rationing in markets with imperfect information, *American Economic Review* 71, 393-410.

Stiglitz, J.E. and A. Weiss (1983), Incentive effects of terminations: Applications to the credit and labor markets, *American Economic Review* 73, 912-927.

Stott, H.P. (2006), Cumulative prospect theory's functional menagerie, *Journal of Risk and Uncertainty* 32, 101-130.

Strotz, R.H. (1955), Myopia and inconsistency in dynamic utility maximization, *Review of Economic Studies* 23(3), 165-180.

Stulz, R.M. and R. Williamson (2003), Culture, openness, and finance, *Journal of Financial Economics* 70(3), 313-349.

Suantak, L., F. Bolger and W.R. Ferrell (1996), The 'hard-easy effect' in subjective probability calibration, *Organizational Behavior and Human Decision Processes* 67, 201-221

Subrahmanyam, A. (2007), Behavioral Finance: A review and synthesis, *European Financial Management* 14(1), 12-29.

Summers, L.H. (1985), On Economics and Finance, *The Journal of Finance* 40(3), 633-635.

Summers, L.H. (1986), Does the stock market rationally reflect fundamental values? *Journal of Finance* 41(3), 591-601.

Sunstein, C. (2005), Moral heuristics, *Behavioral and Brain Sciences* 28, 531-573.

Svenson, O. (1981), Are we all less risky and more skillful than our fellow drivers? *Acta Psychologica*, 47, 143-151

Tamari (1966), Financial ratios as a means of forecasting bankruptcy, *Management International Review* 4, 189-199.

Taylor, S.E. (1982b), The availability bias in social perception and interaction, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Taylor, S.J. (1982a), Tests of the random walk hypothesis against a price-trend hypothesis, *The Journal of Financial and Quantitative Analysis* 17(1), 37-61.

Thaler, R.H. (1980), Toward a positive theory of consumer choice, *Journal of Economic Behavior & Organization* 1(1), 39-60.

Thaler, R.H. (1981), Some empirical evidence on dynamic inconsistency, *Economic Letters* 8(3), 201-207.

Thaler, R.H. (1983), Illusions and mirages in public policy, *Public Interest* 73, 60-74. Reprinted in H. Arkes and K. Hammond (eds.), *Judgment and Decision Making: An Interdisciplinary Reader*, Cambridge University Press.

Thaler, R.H. (1985), Mental accounting and consumer choice, *Marketing Science* 4(3), 199-214.

Thaler, R.H. (1990), Anomalies: Saving, fungibility, and mental accounts, *Journal of Economic Perspectives* 4(1), 193-205.

Thaler, R.H. (1992), *The Winner's Curse: Paradoxes and Anomalies of Economic Life*, Princeton University Press.

Thaler, R.H. (1993), *Advances in Behavioral Finance*, Russell Sage Foundation.

Thaler, R.H. (1999a), The end of behavioral finance, *Financial Analysts Journal* 55(6), 1-17.

Thaler, R.H. (1999b), Mental accounting matters, *Journal of Behavioral Decision Making* 12(3), 183-206.

Thaler, R.H. (2008), Mental accounting and consumer choice: Anatomy of a failure, *Marketing Science* 27(1), 12-14.

Thaler, R.H. and C. Sunstein (2003), Libertarian Paternalism, *The American Economic Review* 93, 175–179.

Thaler, R.H. and E.J. Johnson (1990), Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice, *Management Science* 36(6), 643-660.

Thaler, R.H. and H.M. Shefrin (1981), An economic theory of self-control, *Journal of Political Economy* 89(2), 392-406.

Thaler, R.H. and S. Benartzi (2001), Save more tomorrow: Using behavioral economics to increase employee saving, *Journal of Political Economy* 112(1), S164-S187.

Thaler, R.H., A. Tversky, D. Kahneman and A. Schwartz (1997), The effect of myopia and loss aversion on risk: Taking an experimental test, *Quarterly Journal of Economics* 112(2), 646-661.

Thompson, R.G., L.N. Langemeier, C.T. Lee, E. Lee and R.M. Thrall (1990), The role of multiplier bounds in efficiency analysis with application to Kansas farming, *Journal of Econometrics* 46, 93-108.

Thrall, R.M. (1999), What is the Economic Meaning of FDH? *Journal of Productivity Analysis* 11, 243-250.

Thurstone, L.L. (1927), A law of comparative judgment, *Psychological Review* 34, 273-286.

Tinbergen, J. (1930), Bestimmung und Deutung von Angebotskurven. Ein Beispiel, *Zeitschrift für Nationalökonomie* I.

Tirole, J. (1982), On the possibility of speculation under rational expectations, *Econometrica* 50, 1163-81.

Tirole, J. (1985), Asset bubbles and overlapping generations, *Econometrica* 53(6), 1499-1528.

Tobin, J. (1958), Liquidity preference as behavior toward risk, *Economic Studies* 25, 65-86.

Tobin, J. (1965), The theory of portfolio selection, In F.H. Hahn and F.P.R. Brechling (eds.), *The Theory of Interest Rates*, Macmillan.

Todd, P.M. and Miller, G.F. (1999), From pride and prejudice to persuasion: Satisficing in mate search, in G. Gigerenzer, P.M. Todd and the ABC Research Group (1999), *Simple Heuristics That Make Us Smart*, Oxford University Press.

Townsend, R. (1979), Optimal contracts and competitive markets with costly state verification, *Journal of Economic Theory* 21, 265-293.

Treynor, J.L. (1965), How to rate management of investment funds, *Harvard Business Review* 43, 63-75.

Trivers, R.L. (1971), The evolution of reciprocal altruism, *Quarterly Review of Biology* 46, 35-57.

Trivers, R.L. (2011), *The Folly of Fools: The Logic of Deceit and Self-Deception in Human Life*, Basic Books.

Trivoli, G.W. (1980), How to profit from insider trading information, *Journal of Portfolio Management* 6, 51-56.

Trueman, B (1994), Analyst forecasts and herding behavior, *Review of Financial Studies* 7, 97–124.

Tversky, A. (1972), Elimination by aspects: A theory of choice, *Psychological Review* 76, 281-299.

Tversky, A. and D. Kahneman (1971), The belief in the law of small numbers, *Psychological Bulletin* 76(2), 105-110.

Tversky, A. and D. Kahneman (1973), Availability: A heuristic for judging frequency and probability, *Cognitive Psychology* 5(2), 207-232. Reprinted in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Tversky, A. and D. Kahneman (1974), Judgment under uncertainty: Heuristics and biases, *Science* 185(4157), 1124-31.

Tversky, A. and D. Kahneman (1980), Causal schemas in judgments under uncertainty, Reprinted short version in D. Kahneman, P. Slovic and A. Tversky (1982), *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Tversky, A. and D. Kahneman (1981), The framing of decisions and the psychology of choice, *Science* 211(4481), 453-458.

Tversky, A. and D. Kahneman (1982a), Evidential impact of base rates, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Tversky, A. and D. Kahneman (1982b), Judgments of and by representativeness, In D. Kahneman, P. Slovic and A. Tversky, *Judgment Under Uncertainty: Heuristics and Biases*, Cambridge University Press.

Tversky, A. and D. Kahneman (1983), Extension versus intuitive reasoning: The conjunction fallacy in probability judgment, *Psychological Review* 90(4), 293-315.

Tversky, A. and D. Kahneman (1986), Rational choice and the framing of decisions, *The Journal of Business* 59(S4), S251-S278.

Tversky, A. and D. Kahneman (1991), Loss aversion in riskless choice: A reference-dependent model, *The Quarterly Journal of Economics* 106(4), 1039-61.

Tversky, A. and D. Kahneman (1992), Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5(4), 297-323.

Tversky, A. and E. Shafir (1992), The disjunction effect in choice under uncertainty, *Psychological Science* 3(5), 305–309.

Van Boven, L. and N. Epley (2003), The unpacking effect in evaluative judgments: When the whole is less than the sum of its parts, *Journal of Experimental Social Psychology* 39, 263–269.

Vayanos, D. and P. Wooley (2013), An Institutional Theory of momentum and reversal, *Review of Financial Studies* 26(5), 1087-1145.

Veronesi, P. (1999), Stock market overreaction to bad news in good times: A rational expectations equilibrium model, *Review of Financial Studies* 12 (5), 975-1007.

Viera, A.J. and S.I. Bangdiwala (2007), Eliminating bias in randomized controlled trials: Importance of allocation concealment and masking, *Family Medicine* 39(2), 132-137.

Von Eije, H. and W.L. Megginson (2008), Dividends and share repurchases in the European Union, *Journal of Financial Economics* 89(2), 347-374.

Von Neumann, J. and O. Morgenstern (1944), *Theory of Games and Economic Behavior*, Princeton University Press.

Wachtel, S. (1942), Certain observation on seasonal movement in stock prices, *Journal of Business* 15, 184-193.

Wakker, P.P. (2008), Explaining the characteristics of the power (CRRA) utility family, *Health Economics* 17, 1329-44.

Wakker, P.P. (2010), *Prospect Theory for Risk and Ambiguity*, Cambridge University Press.

Wakker, P.P. and A. Tversky (1993), An axiomatization of cumulative prospect theory, *Journal of Risk and Uncertainty* 7, 147-176.

Wakker, P.P. and D. Deneffe (1996), Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown, *Management Science* 42, 1131-50.

Wall, A. and R.W. Dunning (1928), *Ratio Analysis of Financial Statements,* New York: Harper Brothers.

Warfield, T.D. and J.J. Wild (1992), Accounting recognition and the relevance of earnings as an explanatory variable for returns, *Accounting Review* 67(4), 821-842.

Weber, M. (1905), *The Protestant Ethic and the Spirit of Capitalism*, Routledge Classic, London (2001).

Weinstein, N.D. and W.M. Klein (1995), Resistance of personal risk perceptions to debiasing interventions, *Health Psychology* 14(2), 132-140.

Weitzman, M. (2007), Structural uncertainty and the value of statistical life in the economics of catastrophic climate change, *NBER Working Papers 13490*.

Welch, I. (2000), Herding among security analysts, *Journal of Financial Economics* 58, 369–96.

Welch, I. (2004), Capital structure and stock returns, *Journal of Political Economy* 112(1), 106-132.

Wermers, R. (1999), Mutual fund herding and the impact on stock prices, *The Journal of Finance* 54(2), 581-622.

West, K.D. (1988a), Dividend innovation and stock price volatility, *Econometrica* 56(1), 36-71.

West, K.D. (1988b), Bubbles, fads and stock price volatility tests: a partial view, *Journal of Finance* 43, 639-656.

Wiener, J. and T. Doescher (2008), A framework for promoting retirement savings, *The Journal of Consumer Affairs* 42(2), 137-164.

Williams, E.F. and T. Gilovich (2008), Do people really believe they are above average? *Journal of Experimental Social Psychology* 44(4), 1121-28.

Windschitl, P.D., J. Kruger and E. Simms (2003), The influence of egocentrism and focalism on people's optimism in competitions: When what affects us equally affects me more, *Journal of Personality and Social Psychology* 85(3), 389-408.

Woodland, L.M. and B.M. Woodland (1994), Market efficiency and the favorite-longshot bias: The baseball betting market, *Journal of Finance* 49(1), 269-279.

Worthington, A.C. and H. Higgs (2009), Efficiency in the Australian stock market, 1875-2006: A not on extreme long run random walk behavior, *Applied Economics Letters* 16(3), 301-306.

Wray, L.R. (2007), Endogenous money: Structuralist and horizontalist, *The Levy Economics Institute*, working paper no. 512.

Wu, G. and R. Gonzalez (1996), Curvature of the probability weighting function, *Management Science* 42(12), 1676-1690.

Wurgler, J. and K. Zhuravskaya (2002), Does arbitrage flatten demand curves for stocks? *Journal of Business* 75(4), 583-608.

Xiao, X. (2011), Bank-based versus market-based financial systems: Effect on financial markets, *Management and Service Science (MASS)*, 2011 International Conference on, DOI 10.1109/ICMSS.2011.5998506

Xiong, W. (2001), Convergence trading with wealth effects: An amplification mechanism in financial markets, *Journal of Financial Economics* 62, 247-292.

Xiong, W., and J. Yu (2011), The Chinese warrants bubble, *American Economic Review* 101, 2723-53.

Yaari, M.E. (1987), The dual theory of choice under risk, *Econometrica* 55(1), 95-115.

Yoon, C., C.A. Cole and M.P. Lee (2009), Consumer decision making and aging: Current knowledge and future directions, *Journal of Consumer Psychology* 19(1), 2-16.

Yuan, K., L. Zheng and G. Zhu (2006), Are investors moonstruck? Lunar phases and stock returns, *Journal of Empirical Finance* 13(1), 1-23.

Zak, P.J. (2011), The physiology of moral sentiments, *Journal of Economic Behavior & Organization* 77, 53-65.

Zarowin, P. (1989), Does the stock market overreact to corporate earnings information? *Journal of Finance* 44, 1385-1400.

Zarowin, P. (1990), Size, seasonality, and stock market overreaction, *Journal of Financial and Quantitative Analysis* 25, 113-125.

Zeckhauser, R., J. Patel and D. Hendricks (1991), Nonrational actors and financial market behavior, *Theory and Decision* 31, 257-287.

Zeelenberg, M., J. Beattie, J. van der Pligt and N.K. de Vries (1996), Consequences of regret aversion: Effects of expected feedback on risky decision making, *Organizational Behavior and Human Decision Processes* 65(2), 148-158.

Zell, E. and M.D. Alicke (2011), Age and the better-than-average, *Journal of Applied Social Psychology* 41(5), 1175-88.

Zitzewitz, E. (2001), Measuring herding and exaggeration by equity analysts, *Working Paper*, Graduate School of Business, Stanford University.

Zuckerman, M., S. Eysenck and H. Eysenck (1978), Sensation seeking in England and America: Cross-cultural, age, and sex comparisons, *Journal of Consulting and Clinical Psychology* 46, 139–149.

Zweig, M.E. (1973), An investor expectations stock price predictive model using closed-end fund premiums, *Journal of Finance* 28(1), 67-78.

APPENDICES

APPENDIX EXPERIMENTAL RESEARCH

In this Appendix we detail the technical specifications of the statistical analyses implemented in the experimental research —Chapters 7 and 8. In addition, we provide some supplementary information regarding the following instances. First, the behavioral tests described in Chapter 7, such as the questionnaire on demographic information participants had to complete, a sample of questions in the trivia and confidence interval tests, and raw data of the participants' responses in the different behavioral tests. Second, some supplementary statistical information for the hypothesis testing in Chapter 7 is provided regarding the regression models and others. Finally, some supplementary statistical information to the business game in Chapter 8 regarding raw data of the participants' responses, regression models and others is provided as well.

Statistical analysis. Technical specifications

IBM SPSS Statistics version 21 was used for statistical analysis. Technical specifications, provided by the statistical package, of the analyses implemented are in order.

The tests of Normality implemented were the Kolmogorov–Smirnov test with the Lillefors Significance Correction, and the Shapiro–Wilk test. Additionally, the probability distributions of each variable were compared against a Normal distribution using Q-Q plots and box-and-whiskers plots. All statistical regressions used a stepwise procedure for variable selection that applies the criteria "Probability of F to enter ≤ 0.05; probability of F to remove ≥ 0.10". The number of observations to be included in the regression considered a 'missing pairwise' criteria in all instances.

Factorial analyses considered the following specifications. The extraction method used was a Principal Component Analysis (PCA) of the correlation matrix. Descriptive measures provided are the Kaiser–Meyer–Olkin measure of sampling adequacy (KMO) and the Bartlett's test of Sphericity. The rotated component matrix was obtained using a Varimax normalization as the rotation method. Finally, Cluster analyses consider the average linkage between groups as a method of clustering and the squared Euclidean distance as a measure.

R Project (R Core Team, 2012) was also used for the following purposes. rriskDistributions package (Belgorodski et al., 2012) was used to fit beta distributions to the interval estimates provided by respondents. zipfR package (Evert and Baroni, 2007) was used to estimate the expected absolute deviation (EAD) of the estimated beta functions.

R Core Team (2012). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Belgorodski, N., M. Greiner, K. Tolksdorf and K. Schueller (2012), rriskDistributions: Fitting distributions to given data or known quantiles. R package version 1.8. http://CRAN.R-project.org/package=rriskDistributions

Evert, S. and M. Baroni (2007), zipfR: Word frequency distributions in R, In Proceedings of the 45th Annual Meeting of the Association for Computational Linguistics, Posters and Demonstrations Sessions, 29-32. (R package version 0.6-6 of 2012-04-03)

Raw data and supplementary statistical information

In the Appendix to the experimental research that follows we provide five pieces of information. First, Tables A.1 to A.4 provide some additional information regarding the behavioral tests described in Chapter 7. These include the questionnaire on demographic information participants had to complete, a sample of questions in the trivia and confidence interval tests, and the sets of prospects and sure outcomes from which the questions in the risk profiler were removed from. Questions and questionnaires in the original tests were either in Spanish or Galician languages. Here a translation into English is provided.

Second, Tables A.5 and A.6 provide the raw data of the responses provided by the participants in the experiment and the behavioral variables that were estimated in consequence.

Third, Tables A.7 to A.11 provide some additional statistical information not included in Chapter 7 regarding histograms, normal Q-Q plots and box-and-whisker plots of the behavioral variables, ANOVA tests and regression models.

Fourth, Tables A.12 and A.13 provide the raw data of the strategies implemented by participants in the business simulation game in Chapter 8.

Fifth, Tables A.14 to A.18 provide some additional statistical information not included in Chapter 8 regarding histograms, normal Q-Q plots and box-and-whisker plots of the game indicators, regression models of game indicators to behavioral variables, correlations among variables and factors, and regression models of variables and factors of three instances: game factors to behavioral factors, game factors to behavioral variables, and game indicators to behavioral factors.

TABLE A.1 – Questionnaire for 'Priors'

Sexo	☐ Muller	☐ Home
Idade	☐ Anos	
Estudos *(1)*	☐ 1º de Grao	☐ 4º de Grao
	☐ 2º de Grao	☐ 5º de Licenciatura
	☐ 3º de Grao	☐ 6º de Licenciatura (Dobre)
		☐ Mestrado / MBA
Facultade	☐ Economía e Empresa, UDC	☐ Economía e Empresa, USC
	☐ Informática	☐ Filoloxía
	☐ CC Educación	☐ Dereito
Experiencia profesional	☐ Sen experiencia	☐ Prácticas académicas
	Con experiencia laboral remunerada de…	☐ … menos de 1.000 eur /mes
		☐ … máis de 1.000 eur /mes

(1) Indique o curso máis alto no que está matriculado actualmente

TABLE A.2 – Sample of questions in the Trivial test

1	**Quen interpretaba o papel do estudante Marty McFly na comedia de ciencia ficción "Back to the future" ("Regreso ao futuro"), de 1985?**			
		☐ Christopher Lloyd ☐ Robert Zemeckis	☐ Tom Hanks ☐ Michael J. Fox	☐ Outra resposta
2	**Cincenta, A Sereíña, Aladino ou O Rei León son películas producidas todas elas por que famosa compañía?**			
		☐ Disney ☐ Time Warner	☐ Sony ☐ Metro Goldwyn Mayer	☐ Outra resposta
3	**Que actor, ex-marido de Nicole Kidman, protagonizou entre outras as películas Rain Man, Minority Report, Mission Impossible e Jerry Maguire?**			
		☐ Daniel Day-Lewis ☐ Sean Penn	☐ Tom Cruise ☐ Adrien Brody	☐ Outra resposta
4	**Que filme protagonizado por Hilary Swank e Clint Eastwood gañou o Oscar da Academy á mellor película en 2005?**			
		☐ Infiltrados ('The Departed') ☐ Million Dollar Baby	☐ Brokeback Mountain ☐ Sen perdón ('Unforgiven')	☐ Outra resposta
5	**Que famoso compositor clásico escribíu nove sinfonías -sendo a máis coñecida a Quinta- e quedou sordo nos últimos anos da súa vida?**			
		☐ Joseph Haydn ☐ Gustav Mahler	☐ Wolfgang Amadeus Mozart ☐ Antonio Vivaldi	☐ Outra resposta

TABLE A.3 – Questions on interval estimates

1 En que ano foi patentada a primeira máquina de vapor?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que fose tanto antes como despois do ano [ ]
Estou un 90% seguro/a de que foi DESPOIS DO ANO [ ]
Estou un 90% seguro/a de que foi ANTES DO ANO [ ]

2 En que ano foi inventado o telégrafo?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que fose tanto antes como despois do ano [ ]
Estou un 90% seguro/a de que foi DESPOIS DO ANO [ ]
Estou un 90% seguro/a de que foi ANTES DO ANO [ ]

3 Canta xente morreu en todo o mundo durante 2006 debido a ataques de tiburón?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que fose tanto máis como menos de [ ] mortes
Estou un 90% seguro/a de que foron MÁIS DE [ ] mortes
Estou un 90% seguro/a de que foron MENOS DE [ ] mortes

4 Canta xente morreu en España durante 2006 en accidentes de tráfico?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que fose tanto máis como menos de [ ] mortes
Estou un 90% seguro/a de que foron MÁIS DE [ ] mortes
Estou un 90% seguro/a de que foron MENOS DE [ ] mortes

5 Cantos minutos se tarda en ir andando a un ritmo moderado (5 km/h) desde a praza de María Pita á Torre de Hércules?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que se tarde tanto máis como menos de [ ] minutos
Estou un 90% seguro/a de que se tarda MÁIS DE [ ] minutos
Estou un 90% seguro/a de que se tarda MENOS DE [ ] minutos

6 Cantos minutos se tarda en ir andando a un ritmo moderado (5 km/h) desde o Monte do Gozo á praza do Obradoiro?
Facilite ademáis un valor mínimo e un valor máximo que lle permitan estar seguro/a da súa resposta ao 90%

Coido que é TAN PROBABLE que se tarde tanto máis como menos de [ ] minutos
Estou un 90% seguro/a de que se tarda MÁIS DE [ ] minutos
Estou un 90% seguro/a de que se tarda MENOS DE [ ] minutos

Correct answers: *The first commercial steam-powered device was a water pump, developed in 1698 by Thomas Savery (see Wikipedia, http://en.wikipedia.org/wiki/Steam_engine, last access oct-2013). We consider 1837 the year of the invention of the telegraph, though in the 1830s several devices were invented. For further information see wikipedia (http://en.wikipedia.org/wiki/Electrical_telegraph, last access oct-2013). Regarding shark attacks, we borrow that question from Shefrin (2008), who reports a correct answer of only four deaths. The Spanish DGT at http://www.dgt.es/portal/es/seguridad_vial/estadistica/accidentes_24horas/evolucion_n_victimas/ provides yearly statistics about the number of deaths in the Spanish roads. The number of deaths reported for 2006 was 2989 (last access oct-2013). The minutes required to walk from the places in A Coruña and Santiago de Compostela mentioned in the tests above was estimated using GoogleMaps to calculate distances. At a moderate speed of 5 km/h the times required would be 23 minutes from María Pita to Torre de Hércules, and 55 minutes from Monte do Gozo to Praza do Obradoiro.*

TABLE A.4 – Prospects and sure outcomes for the CPT risk-profiler

	y_i	x_i	p_g				AS_{-1}				AS_0						AS_{+1}								CHECK
Q1	0	10.000	50%	serie 1	50		195				720						2.685						10.000		
						125			370	545			1.375	2.030				3.730	4.775	5.820	6.865	7.910		serie 2	última serie 1
Q_{prueba}	0	20.000	50%	serie 1	70		290				1.180						4.860						20.000		SAMPLE QUEST.
						180			585	885			2.405	3.636				7.025	9.185	11.350	13.510	15.675		serie 2	última serie 1
Q2	0	5.000	50%	serie 1	40		130				440						1.480						5.000		
						85			235	340			790	1.135				1.980	2.485	2.990	3.490	3.995		serie 2	última serie 1
Q3	0	20.000	99%	serie 1	1.180						4.860												20.000		
										3.020		7.385	9.905	12.430	14.955	17.480								serie 2	última serie 1
Q4	0	5.000	95%	serie 1	440						1.480												5.000		
										960		2.065	2.655	3.240	3.825	4.415								serie 2	última serie 1
Q5	0	10.000	5%	serie 1	50						195						720						2.685		
										125			325	460	590			1.000	1.280	1.560	1.840	2.125		serie 2	última serie 1
Q6	0	20.000	1%	serie 1	20						70						290						1.180		
										45			125	180	235			415	545	670	800	925		serie 2	última serie 1

	y_i	x_i	p_l				AS_{-1}				AS_0						AS_{+1}								CHECK
Q9	0	-10.000	50%	serie 1	-50		-195				-720						-2.685						-10.000		
						-125			-370	-545			-1.375	-2.030				-3.730	-4.775	-5.820	-6.865	-7.910		serie 2	última serie 1
Q_{prueba}	0	-20.000	50%	serie 1	-70		-290				-1.180						-4.860						-20.000		SAMPLE QUEST.
						-180			-585	-885			-2.405	-3.636				-7.025	-9.185	-11.350	-13.510	-15.675		serie 2	última serie 1
Q10	0	-5.000	50%	serie 1	-40		-130				-440						-1.480						-5.000		
						-85			-235	-340			-790	-1.135				-1.980	-2.485	-2.990	-3.490	-3.995		serie 2	última serie 1
Q7	0	-10.000	5%	serie 1	-50		-195				-720												-2.685		
						-125		-325	-460	-590		-1.000	-1.280	-1.560	-1.840	-2.125								serie 2	última serie 1
Q8	0	-20.000	1%	serie 1	-20		-70				-290												-1.180		
						-45		-125	-180	-235		-415	-545	-670	-800	-925								serie 2	última serie 1
Q11	0	-20.000	99%	serie 1	-1.180						-4.860												-20.000		
										-3.020		-7.385	-9.905	-12.430	-14.955	-17.480								serie 2	última serie 1
Q12	0	-5.000	95%	serie 1	-440						-1.480												-5.000		
										-960		-2.065	-2.655	-3.240	-3.825	-4.415								serie 2	última serie 1

TABLE A.5 – Raw data from Behavioral Tests (1/3)

	PRIORS					TRIVIAL																													
	p1	p2	p3	p4	p5	a1	a2	a3	a4	b1	b2	b3	b4	c1	c2	c3	c4	min1	max1	med1	min2	max2	med2	min3	max3	med3	min4	max4	med4	min5	max5	med5	min6	max6	med6
1	1	18	1	1	1	6	3	4	4	7	4	4	4	7	5	7	6	1700	1800	1736	1800	1850	1816	300	700	367	20	100	83	10	40	25	10	50	35
2	1	18	1	1	3	6	0	5	7	8	1	5	8	7	5	7	7	1781	N/A	N/A	1781	N/A	N/A	20	N/A	N/A	10000	N/A	N/A	N/A	N/A	40	60	N/A	N/A
3	1	18	1	1	1	4	4	3	6	6	1	1	3	6	4	4	6	1800	1850	1810	1900	1960	1900	400	600	500	5000	12000	10000	15	30	20	10	20	15
4	1	18	1	1	1	3	2	2	3	5	2	2	2	6	3	3	3	1800	1900	1800	1900	1950	1900	10	20	20	500	1000	500	10	20	20	20	40	30
5	1	19	2	1	3	6	2	6	5	10	7	10	10	6	4	5	7	1700	1800	1745	1800	1900	1890	5	25	16	1000	5000	3500	10	30	20	30	60	45
6	1	19	2	1	1	3	4	2	3	3	1	3	3	5	3	7	7	1700	2000	1750	1500	1999	1650	100	500	250	100	800	200	20	60	30	20	60	45
7	1	19	2	1	1	6	3	2	5	7	2	4	7	6	4	5	7	1950	1960	1955	1915	1925	1920	50	100	75	170	300	200	10	20	15	15	30	20
8	1	19	4	1	1	4	2	2	5	5	2	2	4	5	3	3	4	1730	1880	1866	1700	1750	1713	20	40	30	230	300	250	20	45	30	50	90	75
9	1	19	3	1	1	5	2	3	6	8	1	3	6	7	5	6	7	1750	1900	1850	1850	1912	1870	2	10	7	50	100	79	20	60	30	40	80	50
10	1	19	2	2	1	6	1	2	4	8	1	4	6	7	2	6	7	1500	1650	1600	1550	1690	1650	6	26	15	100	200	150	15	25	20	20	40	30
11	1	19	2	6	1	7	2	4	6	7	3	6	5	7	5	5	5	1760	1855	1830	1670	1800	1720	2	10	6	10000	19000	15500	20	40	26	40	115	95
12	1	19	2	6	1	7	2	2	7	7	2	3	7	4	5	5	7	1700	1850	1800	1650	1800	1700	5	100	20	300	5000	1000	15	35	25	5	60	30
13	1	20	4	1	1	7	2	4	4	6	1	3	6	6	3	5	6	1850	1950	1900	1700	1975	1800	50	200	100	200	700	400	15	50	30	30	90	50
14	1	20	3	1	1	4	4	4	3	7	2	2	5	6	5	4	6	1800	1900	1800	1800	1900	1800	20	60	50	1000	4000	1000	100	200	150	100	200	150
15	1	20	3	1	1	5	3	4	6	6	3	3	7	5	4	5	8	1700	1900	1850	1000	1900	1700	20	2000	500	500	5000	2000	20	60	30	10	60	30
16	1	20	3	1	1	6	4	3	3	6	1	4	5	5	4	4	6	1800	1900	1843	1300	1600	1505	5	20	15	100	300	250	15	30	20	15	35	30
17	1	20	1	2	1	4	2	2	3	5	1	2	3	7	3	5	6	1750	1950	1800	1650	1850	1750	130	350	200	600	1000	800	10	30	15	100	190	120
18	1	21	1	1	1	2	0	4	4	5	3	4	7	6	4	5	8	1750	1760	1760	1620	1640	1630	900	1E+06	1E+06	300	450	400	10	20	15	15	30	20
19	1	21	4	1	1	6	4	1	6	5	2	5	7	5	3	4	6	1790	1890	1820	1800	1900	1850	15	50	30	600	1000	750	10	30	20	30	50	40
20	1	21	4	1	1	5	4	4	7	6	2	4	6	7	2	4	6	1918	1925	1920	1750	1875	1800	180	220	200	22000	29000	25000	22	30	25	20	40	32
21	1	21	4	1	1	6	1	3	4	8	2	5	6	8	5	6	7	1800	1900	1880	1685	1800	1700	45000	70000	50000	5E+06	7E+06	5E+06	20	35	30	85	120	90
22	1	21	4	1	1	6	2	3	4	5	1	2	3	5	3	5	5	1650	1860	1790	1700	1900	1810	300	1000	500	1000	5000	2000	15	35	20	15	40	30
23	1	21	4	1	1	2	2	2	4	5	3	3	5	7	5	5	6	1800	1850	1810	1700	1750	1720	2	10	5	120	200	150	20	60	35	15	40	20
24	1	21	7	1	2	3	4	0	4	4	1	3	4	5	4	4	5	1860	1940	1925	1920	1950	1940	0	5	2	30	120	80	15	35	20	15	25	20
25	1	21	7	1	2	6	2	3	6	6	4	7	6	6	5	6	6	1890	1920	1900	1900	1915	1912	25	800	100	150	1000	500	20	60	45	40	130	70
26	1	21	7	1	2	4	2	1	6	5	2	2	5	7	4	5	7	1850	1890	1870	1860	1900	1880	1350	2000	1750	40000	85000	50000	4	8	5	8	14	10
27	1	21	1	2	3	3	1	2	1	4	2	4	4	7	3	6	6	1400	1700	1600	1500	1800	1700	5	30	20	10	100	50	100	300	200	100	400	300
28	1	22	1	1	3	5	2	3	6	6	4	6	8	6	4	6	8	1750	1900	1800	1800	1950	1850	5000	30000	10000	1000	10000	4000	40	90	75	40	90	70
29	1	22	3	1	4	6	3	2	7	5	1	3	3	5	3	4	5	1750	1900	1850	1800	1950	1900	10	100	50	100	500	300	20	60	40	20	120	60
30	1	22	4	1	2	7	2	2	3	7	2	4	5	6	2	5	6	1800	1900	1850	1900	1980	1950	1	3	2	100	250	170	20	90	40	60	200	120
31	1	22	4	1	2	2	0	1	4	4	0	2	4	5	2	4	5	1700	1900	1800	1600	1950	1850	500	2000	1000	100	250	200	20	40	30	20	60	40
32	1	22	6	1	3	9	3	5	7	7	4	5	6	6	6	5	7	1780	1848	1800	1790	1900	1850	10	60	30	200	500	300	13	25	18	15	30	22
33	1	22	7	1	2	5	1	1	2	5	0	3	4	7	4	5	7	1800	1910	1900	1700	1900	1850	0	15	10	200	500	320	10	60	30	45	120	60
34	1	22	7	1	3	4	0	3	3	4	1	3	3	4	3	4	4	1400	1600	1500	1650	1800	1700	5000	15000	7000	400	650	600	20	45	30	30	55	45
35	1	22	4	1	2	10	1	5	7	8	3	6	6	8	6	7	7	1680	1750	1710	1850	1920	1880	10	100	50	50	150	80	30	180	120	30	180	100
36	1	22	7	1	2	6	0	4	4	8	8	6	5	9	7	9	7	650	1900	1800	500	1800	1700	1	1E+06	50	50	2500	100	1	90	5	30	180	40
37	1	23	1	1	2	5	2	2	5	7	2	1	4	8	5	3	6	1000	2000	1500	1000	2000	1600	100	1000	500	500	10000	900	15	60	30	45	120	60
38	1	23	1	1	3	6	2	4	8	8	2	6	7	9	5	8	9	1790	1800	1790	1800	1850	1800	2	50	45	1	350	300	5	20	15	5	60	40
39	1	23	4	1	4	5	2	1	4	5	2	0	4	7	2	1	7	1550	1650	1600	1850	1900	1870	1	3	2	100	200	150	40	60	45	40	70	50
40	1	23	7	1	2	4	0	3	7	7	1	1	6	6	5	4	7	1450	1600	1500	1380	1500	1400	12	100	50	250	500	450	30	60	45	60	120	90
41	1	23	4	1	2	3	2	3	5	6	2	2	5	6	1	1	5	1700	1850	1800	1600	1800	1700	40	200	100	100	250	200	30	80	60	50	120	70
42	1	23	7	1	2	6	5	0	5	7	2	3	5	7	5	5	6	1600	1800	1789	1400	1800	1600	30	80	50	100	1000	200	20	60	30	30	100	60
43	1	23	7	1	3	8	1	2	6	5	1	0	6	4	2	3	7	1800	1950	1900	1850	1960	1950	2	60	50	50	150	100	30	180	150	60	240	180
44	1	23	4	1	1	6	0	1	6	6	1	3	9	7	5	6	9	1700	1900	1875	1600	1900	1850	0	100	20	20	1000	500	10	45	30	20	120	60

	PROSPECT THEORY														
	1+	2+	3+	4+	5+	6+	1-	2-	3-	4-	5-	6-	β1	β2	β3
1	688	268	1,890	330	160	58	-63	-14	-95	-43	-1,005	-115	2	15	130
2	335	185	1,228	115	240	218	-343	-208	-43	-105	-1,450	-230	2	17	160
3	910	458	1,228	475	108	113	-108	-14	-125	-60	-565	-330	2	15	200
4	510	310	1,890	475	43	22	-343	-14	-125	-78	-1,670	-175	3	25	250
5	420	185	1,890	425	108	58	-63	-14	-180	-105	-1,005	-280	2	15	170
6	510	225	1,450	378	43	22	-63	-22	-420	-225	-1,670	-378	10	50	1,000
7	420	185	1,228	280	108	14	-43	-14	-95	-30	-1,005	-175	3	14	180
8	688	310	1,890	378	160	88	-28	-14	-28	-20	-565	-475	2	20	500
9	510	310	1,670	330	28	88	-28	-14	-65	-30	-785	-175	5	40	350
10	600	268	1,450	378	315	218	-85	-58	-258	-43	-1,005	-115	3	40	300
11	420	268	1,890	425	63	43	-43	-14	-420	-185	-1,890	-425	2	30	600
12	420	145	1,890	378	43	14	-28	-22	-420	-268	-1,890	-425	5	50	7,000
13	510	268	343	425	28	14	-43	-30	-420	-60	-1,005	-475	1	20	800
14	910	395	1,890	425	108	88	-28	-14	-125	-145	-1,890	-425	1	10	150
15	775	395	1,890	378	240	140	-63	-22	-258	-30	-1,890	-475	3	15	200
16	510	268	1,890	425	108	58	-63	-58	-180	-105	-1,005	-378	1	10	100
17	510	225	1,890	378	200	88	-28	-14	-335	-185	-1,670	-378	5	50	500
18	510	310	1,890	378	130	88	-28	-14	-65	-43	-1,228	-175	2	15	200
19	688	225	1,890	378	108	168	-43	-14	-95	-43	-1,005	-115	4	60	600
20	910	310	1,890	425	160	14	-28	-14	-28	-20	-1,670	-280	2	20	400
21	775	353	1,890	425	108	58	-63	-58	-510	-268	-1,890	-425	2	25	500
22	910	268	1,890	330	108	43	-28	-22	-95	-60	-1,670	-425	3	30	1,500
23	420	185	1,450	330	43	70	-85	-30	-258	-30	-1,450	-330	2	10	200
24	510	268	1,890	425	240	113	-28	-14	-65	-43	-343	-175	4	15	120
25	420	225	1,670	475	160	70	-28	-14	-95	-60	-1,228	-175	5	35	300
26	420	225	1,670	330	278	218	-28	-14	-180	-60	-1,005	-175	2	20	500
27	258	185	1,890	280	108	88	-63	-30	-258	-185	-1,890	-475	5	10	800
28	510	268	1,890	425	130	88	-43	-30	-420	-43	-1,890	-425	2	40	500
29	600	310	1,670	378	315	218	-130	-130	-95	-78	-1,228	-378	2	30	600
30	510	185	1,228	330	160	22	-43	-30	-420	-145	-785	-378	2	30	1,000
31	775	310	1,890	425	315	218	-223	-108	-420	-145	-1,670	-378	3	100	500
32	335	145	1,450	330	200	140	-43	-30	-258	-43	-785	-175	2	40	700
33	688	353	1,890	425	130	140	-28	-14	-65	-30	-565	-115	1	20	400
34	258	145	1,890	425	63	30	-85	-58	-420	-60	-1,670	-378	5	80	1,100
35	420	268	1,670	378	160	140	-63	-130	-95	-60	-565	-115	1	15	150
36	510	268	1,890	378	43	22	-43	-22	-43	-30	-565	-175	5	50	400
37	688	185	1,890	378	108	43	-108	-108	-420	-145	-1,670	-280	1	20	1,000
38	775	225	1,890	475	200	43	-28	-14	-420	-30	-1,670	-115	1	12	120
39	688	225	1,890	475	28	14	-28	-14	-180	-43	-1,450	-280	2	50	2,000
40	420	78	1,450	378	63	43	-43	-43	-258	-43	-1,670	-425	2	20	500
41	95	105	1,890	378	43	14	-28	-14	-420	-268	-1,890	-425	2	20	120
42	420	353	1,450	425	130	58	-28	-14	-65	-60	-565	-175	5	50	1,000
43	688	310	343	280	355	193	-190	-108	-420	-145	-1,450	-230	5	50	500
44	420	185	785	175	85	30	-28	-30	-420	-225	-1,890	-425	5	40	400

TABLE A.5 – Raw data from Behavioral Tests (2/3)

	PRIORS					TRIVIAL																													PROSPECT THEORY														
	p1	p2	p3	p4	p5	a1	a2	a3	a4	b1	b2	b3	b4	c1	c2	c3	c4	min1	max1	med1	min2	max2	med2	min3	max3	med3	min4	max4	med4	min5	max5	med5	min6	max6	med6	1+	2+	3+	4+	5+	6+	1-	2-	3-	4-	5-	6-	β1	β2	β3
45	1	23	4	1	2	6	2	2	7	5	2	3	8	6	3	5	8	1780	1950	1800	1900	1950	1920	20	300	100	800	4000	2000	15	30	20	15	30	20	335	225	1.890	425	43	43	-28	-30	-180	-60	-1.450	-280	2	20	250
46	1	23	6	1	2	5	0	2	4	7	1	4	4	8	2	5	6	1700	1936	1850	1750	1914	1875	2	20	10	35	100	50	10	25	15	10	60	30	510	268	1.890	475	43	14	-63	-22	-28	-20	-1.890	-425	0,2	9	95
47	1	23	4	1	1	5	0	0	3	5	2	3	3	5	4	6	7	1850	1930	1900	1750	1920	1850	10	30	30	100	300	200	10	40	20	30	60	40	510	225	1.670	378	200	168	-28	-14	-258	-105	-1.670	-330	2	20	200
48	1	23	7	1	2	4	2	4	4	9	3	6	6	7	5	6	5	1800	1912	1900	1800	1950	1900	5	50	25	50	200	100	20	45	30	30	160	100	510	310	1.890	425	160	70	-63	-30	-510	-30	-1.670	-330	2	18	175
49	1	23	7	1	3	5	2	3	4	6	2	3	5	7	5	5	8	1750	1810	1800	1730	1800	1740	150	300	200	230	300	250	10	30	20	60	180	120	420	185	1.890	425	28	14	-28	-14	-420	-185	-1.450	-378	5	50	500
50	1	24	4	1	1	6	2	1	5	7	3	4	7	8	4	5	7	1790	1870	1830	1750	1900	1850	50	150	100	9000	15000	12000	15	40	25	40	80	60	688	458	1.890	378	160	88	-130	-175	-95	-43	-343	-115	2	20	300
51	1	24	6	1	1	8	3	3	7	9	2	4	8	8	3	3	7	1800	1900	1850	1875	1899	1880	5	25	15	250	600	300	12	30	20	30	150	45	510	268	1.890	378	355	168	-43	-58	-600	-310	-1.890	-425	3	30	500
52	1	24	7	1	1	5	1	2	4	4	2	2	6	6	3	4	8	1800	2000	1900	1700	1900	1800	1	20	10	80	150	100	15	60	40	15	40	30	510	185	1.890	378	43	14	-28	-14	-258	-43	-1.670	-175	1	20	250
53	1	24	7	1	2	3	2	1	5	6	3	3	6	7	5	5	8	1850	1900	1900	1700	1900	1800	50	150	100	40500	55000	50000	8	15	10	1000	2000	1500	910	268	1.890	425	160	88	-63	-14	-65	-30	-343	-175	50	100	500
54	1	24	7	3	2	5	2	5	6	7	3	6	8	6	4	5	7	1840	1885	1857	1790	1839	1815	7	21	12	121	167	157	18	28	21	80	150	110	688	268	1.450	330	355	193	-108	-108	-420	-185	-1.890	-475	3	40	800
55	1	24	7	1	2	7	3	3	7	7	2	4	6	6	4	5	7	1740	1800	1760	1850	1900	1860	5	20	10	30	100	70	20	60	45	30	65	50	180	145	785	280	43	14	-43	-22	-95	-60	-1.670	-378	2	25	400
56	1	25	3	1	2	4	4	3	6	4	4	3	5	6	5	6	6	200	1460	865	700	1400	980	100	10000	1003	87	5892	1200	10	25	15	15	45	25	510	268	1.890	378	108	22	-28	-43	-180	-105	-343	-175	1	10	100
57	1	25	7	1	2	6	4	3	6	7	1	2	5	8	5	6	7	1800	1880	1870	1700	1950	1800	10	100	20	170	500	230	15	160	40	60	600	200	910	395	1.890	378	355	113	-28	-14	-43	-20	-343	-175	10	30	500
58	1	26	7	1	3	6	0	2	7	6	2	6	8	7	5	8	8	1800	1900	1860	1800	1900	1850	2000	7000	4000	1500	3000	2500	5	20	10	20	35	25	775	458	1.890	378	315	113	-28	-22	-180	-60	-565	-115	3	25	250
59	1	27	7	1	3	2	1	2	5	3	3	1	5	6	6	4	8	1400	1500	1475	1600	1800	1700	700	1100	1000	500	1000	800	25	45	30	30	60	50	510	268	1.890	378	28	14	-43	-22	-95	-43	-1.670	-280	2	50	120
60	1	28	4	1	4	3	0	2	2	4	1	3	4	7	5	7	8	1800	1900	1870	1850	1950	1920	1	30	15	100	500	200	20	90	50	20	90	50	775	458	1.890	378	130	88	-43	-14	-95	-105	-343	-330	10	25	500
61	2	17	1	1	1	6	2	2	6	9	6	10	7	8	6	9	7	1750	1800	1770	1850	1880	1864	20	80	50	5000	10000	6000	40	80	60	40	80	60	420	105	1.890	378	108	140	-63	-43	-510	-78	-1.450	-175	2	50	5.000
62	2	18	1	1	1	4	4	3	5	5	3	4	4	6	4	4	5	1800	1910	1870	1650	1750	1700	50	200	100	70	200	100	30	60	45	20	60	30	420	185	1.890	378	85	70	-63	-43	-335	-185	-1.890	-378	2	20	300
63	2	18	1	1	1	8	2	7	7	8	3	5	6	7	3	5	6	1850	1970	1865	1850	1950	1895	5	50	20	50	500	100	10	40	20	15	70	30	600	395	1.890	425	108	140	-28	-14	-180	-30	-1.670	-280	2	30	300
64	2	18	1	1	1	6	2	7	9	7	3	2	9	6	3	3	8	1850	1890	1870	1840	1890	1850	25	500	100	500	1500	1000	10	40	25	25	120	90	910	353	1.670	425	278	218	-293	-108	-335	-145	-1.450	-280	2	40	700
65	2	18	1	1	3	6	2	3	7	7	5	3	7	6	6	4	7	1850	1875	1865	1850	1865	1850	10	50	45	1500	2200	1800	15	35	25	25	95	85	335	225	1.670	335	160	14	-108	-85	-420	-78	-1.005	-175	2	25	250
66	2	18	1	1	1	7	1	3	8	8	4	5	8	7	4	5	7	1770	1830	1800	1830	1875	1850	500	1000	739	1000	2000	1300	10	30	20	40	120	60	335	145	1.450	378	108	88	-43	-30	-420	-43	-1.005	-280	1	15	150
67	2	18	2	1	1	9	4	5	4	10	7	8	9	7	6	7	7	1775	1780	1778	1780	1810	1800	40	60	50	1150	1400	1300	40	50	45	40	50	45	510	268	1.890	475	28	14	-28	-14	-28	-20	-1.670	-378	1	10	100
68	2	18	2	2	1	6	2	3	8	9	3	4	6	8	3	4	5	1800	1900	1870	1800	1950	1860	100	400	200	900	2000	1000	30	120	60	45	80	60	420	185	1.890	425	43	22	-28	-14	-65	-20	-1.450	-175	1	10	200
69	2	19	2	2	1	6	1	4	6	8	1	3	6	7	3	4	6	1770	1800	1780	1840	1890	1860	2	7	5	150	300	200	10	25	15	20	50	30	420	145	1.890	425	200	88	-43	-22	-335	-43	-1.890	-425	1	20	400
70	2	19	2	2	1	7	1	5	8	8	3	4	6	7	5	6	7	1750	1850	1800	1800	1900	1850	20	100	50	90	150	100	20	35	25	15	60	35	510	225	1.890	330	43	14	-108	-58	-95	-145	-1.450	-330	2	25	300
71	2	19	1	2	3	5	1	5	4	8	3	6	4	7	4	6	5	1700	1900	1800	1800	1950	1900	250	2000	1000	100000	200000	150000	20	60	45	60	120	90	510	268	1.890	378	108	70	-63	-30	-65	-43	-1.670	-175	2	20	150
72	2	19	2	2	1	7	3	7	4	8	2	6	5	7	4	7	6	1700	1900	1850	1600	1776	1700	5	10	6	500	500000	160000	10	40	20	30	90	60	510	185	1.890	425	108	14	-28	-14	-65	-30	-1.890	-175	2	15	500
73	2	20	1	1	2	5	3	1	6	8	7	10	10	8	6	8	8	1700	1740	1701	1900	1940	1901	10	70	58	1000	5000	4500	10	40	38	20	100	70	180	105	1.890	378	28	14	-130	-70	-910	-458	-1.890	-475	6	40	400
74	2	20	2	1	1	7	4	3	4	8	5	4	6	6	3	2	4	1725	1790	1750	1600	1700	1650	20	350	150	500	1500	800	30	50	40	45	90	60	510	225	1.890	425	28	14	-28	-14	-420	-145	-1.890	-378	2	50	500
75	2	20	2	1	1	5	1	2	5	4	2	3	5	6	5	3	7	1800	1910	1890	1840	1900	1870	1	50	25	150000	300000	200000	15	60	30	90	200	120	510	268	1.890	475	63	22	-28	-70	-28	-20	-785	-115	2	20	200
76	2	20	2	1	1	5	2	2	6	5	1	2	4	5	3	3	5	1800	1820	1810	1920	1950	1933	8	14	10	20	50	30	20	43	30	20	45	30	420	268	1.890	475	28	14	-28	-14	-125	-185	-1.450	-280	2	25	275
77	2	20	2	2	1	2	2	1	7	4	3	2	6	6	6	5	7	1880	1910	1890	1840	1860	1850	2	30	20	20	110	80	10	50	30	25	70	45	510	268	1.890	280	200	218	-28	-14	-510	-185	-1.670	-378	5	25	350
78	2	20	2	2	1	4	2	1	5	7	1	4	5	7	4	5	6	1800	1950	1900	1800	1900	1850	50	600	300	100	1500	600	30	180	120	30	180	120	510	310	1.890	425	315	218	-43	-14	-510	-105	-1.670	-175	3	35	450
79	2	21	4	1	1	4	3	1	5	5	4	4	4	6	4	4	5	1700	1950	1850	1750	1950	1850	15	100	40	50	500	150	15	50	35	15	60	30	510	268	1.670	425	160	88	-85	-43	-420	-225	-1.450	-378	3	40	700
80	2	21	4	1	3	3	2	2	5	5	2	2	6	6	4	5	7	1400	1950	1800	1900	2000	1950	100	200	150	200	600	365	20	60	40	20	60	40	775	395	1.890	475	130	168	-63	-30	-258	-145	-1.890	-425	1	11	105
81	2	21	7	1	2	5	3	2	5	8	2	3	4	6	3	3	4	1800	1950	1900	1800	1950	1900	100	1000	500	200	2000	1000	15	60	30	20	120	45	420	185	1.890	475	28	14	-28	-14	-258	-105	-1.890	-475	2	20	300
82	2	21	4	1	3	7	1	3	5	6	3	5	5	7	5	7	7	1800	1950	1850	1750	1900	1850	35	80	60	1200	2000	1500	20	40	25	20	45	30	600	268	1.890	378	28	14	-28	-14	-43	-43	-1.005	-378	1	10	110
83	2	21	4	1	1	6	3	3	4	8	1	4	6	6	3	4	5	1600	1850	1780	1800	1950	1910	1	20	7	200	1000	350	15	50	35	20	60	40	180	145	1.670	425	28	14	-108	-14	-600	-268	-1.890	-425	2	50	500
84	2	21	2	2	1	5	3	1	5	5	2	3	6	6	4	5	7	1500	1700	1600	1500	1800	1700	3	30	20	70	180	125	35	70	50	50	120	80	420	225	1.450	378	160	88	-43	-58	-180	-60	-1.005	-330	3	30	400
85	2	21	2	2	1	5	2	2	6	8	3	6	8	7	4	6	7	1840	1900	1860	1830	1860	1840	10	20	15	50	90	65	20	40	30	30	60	40	600	268	1.670	330	200	193	-28	-14	-510	-185	-1.890	-425	3	35	500
86	2	21	2	2	4	3	2	4	9	7	4	5	8	6	5	5	6	1750	1810	1780	1800	1900	1850	1000	10000	2500	120	280	180	3	10	7	20	80	50	510	145	1.890	378	43	14	-28	-14	-180	-30	-1.228	-475	1	10	100
87	2	22	1	1	4	7	4	2	9	7	4	6	9	8	3	6	7	1820	1880	1850	1850	1900	1890	10	1000	100	100	500	250	30	60	40	10	50	30	688	268	1.890	378	160	58	-158	-108	-510	-268	-1.890	-425	2	20	250
88	2	22	4	1	1	4	5	3	7	6	3	2	7	6	4	4	7	1760	1850	1808	1800	1950	1900	100	900	350	100	600	300	12	50	30	20	110	45	510	268	1.890	425	85	43	-43	-30	-510	-78	-1.670	-425	2	50	400

TABLE A.5 – Raw data from Behavioral Tests (3/3)

	PRIORS					TRIVIAL																														PROSPECT THEORY														
	p1	p2	p3	p4	p5	a1	a2	a3	a4	b1	b2	b3	b4	c1	c2	c3	c4	min1	max1	med1	min2	max2	med2	min3	max3	med3	min4	max4	med4	min5	max5	med5	min6	max6	med6	1+	2+	3+	4+	5+	6+	1-	2-	3-	4-	5-	6-	β1	β2	β3
89	2	22	4	1	3	7	5	3	7	8	3	6	6	6	2	5	4	1750	1900	1850	1870	1950	1920	1	14	8	75	250	150	10	30	20	10	50	30	510	268	1,890	378	240	168	-63	-14	-180	-105	-1,228	-115	4	50	500
90	2	22	4	1	4	4	2	2	5	8	5	5	8	5	3	3	5	1700	1800	1734	1750	1900	1824	49	149	125	500	1599	1000	12	25	17	10	40	20	910	268	1,890	475	43	14	-28	-14	-420	-78	-1,670	-378	1	15	150
91	2	22	5	1	1	9	3	3	5	8	2	5	7	7	4	5	6	1700	1800	1770	1700	1900	1750	25	500	100	2500	6000	3000	90	200	100	120	400	300	420	225	1,670	425	28	30	-108	-22	-258	-185	-1,450	-378	4	50	600
92	2	22	4	1	1	5	2	1	7	5	3	4	3	3	4	5	5	1700	1900	1800	1600	1900	1700	1000	6000	5000	1000	20000	10000	30	60	40	30	90	60	600	310	1,890	378	108	43	-28	-14	-28	-20	-1,890	-475	2	40	500
93	2	22	4	1	1	5	1	4	5	8	3	4	7	5	4	3	5	1720	1800	1750	1760	1830	1800	20	500	350	1500	2500	2000	15	35	25	20	45	30	510	268	1,890	378	85	22	-43	-30	-510	-268	-1,890	-425	1	10	100
94	2	22	4	1	1	3	2	4	6	6	3	3	4	7	5	6	6	1800	1950	1860	1750	1900	1850	1000	1E+06	10000	1000	10000	2000	10	40	20	10	100	40	420	145	1,890	475	28	22	-28	-14	-125	-78	-1,890	-425	3	50	1,000
95	2	22	7	1	2	6	4	4	6	8	5	4	5	8	6	5	6	1500	1950	1770	1600	1950	1820	2	50	6	20	500	100	20	100	40	15	90	40	420	225	1,890	425	108	58	-63	-43	-420	-268	-1,890	-475	0.9	9	98
96	2	22	7	1	1	10	3	4	9	10	4	4	9	7	3	3	6	1790	1840	1805	1800	1860	1830	500	5000	1000	1000	4000	1200	15	45	20	25	45	35	28	20	343	115	28	14	-343	-208	-180	-105	-1,005	-175	2	15	200
97	2	22	7	1	1	4	2	0	6	5	1	3	4	6	4	4	4	1870	1880	1870	1950	1980	1960	5	5000	500	100	5000	1000	10	240	60	10	240	60	28	20	343	115	28	14	-190	-108	-688	-185	-1,890	-425	10	180	350
98	2	22	3	1	1	3	2	3	5	6	3	4	6	5	4	5	5	1850	1870	1865	1810	1840	1830	9500	30000	15000	500	1100	800	25	35	30	10	30	20	420	185	1,450	175	355	218	-28	-14	-510	-225	-1,670	-230	1	10	100
99	2	22	2	2	1	8	3	4	7	8	2	4	8	8	3	5	8	1740	1800	1780	1800	1910	1850	4	20	10	500	2000	1000	10	40	20	60	240	150	600	225	1,890	378	85	88	-43	-14	-335	-268	-1,450	-378	1	15	200
100	2	23	7	1	2	6	3	2	5	6	4	5	5	6	4	5	5	1000	2000	1900	1000	2000	1920	5	10000	100	15	10000	600	5	300	50	40	600	180	510	268	1,890	475	63	43	-28	-14	-510	-268	-1,890	-475	2	100	500
101	2	23	7	1	1	5	4	5	5	8	5	6	7	7	4	5	5	1800	1900	1875	1775	1850	1800	70	150	100	1800	3000	2000	15	30	22	20	60	40	600	225	1,890	425	200	88	-43	-14	-180	-43	-1,670	-330	2	12	135
102	2	23	4	1	3	7	5	3	8	7	3	2	8	8	4	5	8	1600	1900	1700	1200	1800	1600	30	100	80	175	260	190	25	60	40	35	75	60	420	268	1,890	378	43	14	-28	-14	-258	-145	-1,890	-425	2	15	150
103	2	23	4	1	1	5	0	1	7	7	1	5	6	6	4	4	7	1800	1890	1835	1810	1850	1840	1	60	50	1000	5000	1200	10	20	15	15	30	20	258	225	1,890	475	28	14	-28	-14	-258	-43	-1,228	-280	1	10	100
104	2	23	7	1	1	3	2	1	7	7	5	5	8	6	4	6	8	1550	1720	1640	1700	1900	1815	10	40	24	200	1000	460	60	300	200	200	400	250	420	225	1,450	330	160	140	-158	-22	-258	-145	-565	-230	1	20	250
105	2	23	7	1	2	8	3	3	10	8	3	2	10	7	1	3	7	1750	1900	1850	1700	1850	1800	1000	1E+06	30000	1500	3500	2800	45	150	70	60	200	90	510	268	1,890	378	28	14	-63	-22	-510	-268	-1,890	-425	10	100	1,000
106	2	23	7	1	1	3	1	1	4	4	1	2	3	5	3	2	6	1800	1870	1820	1720	1800	1790	10	80	60	1500	3000	2200	30	120	90	10	90	60	510	310	1,890	475	200	193	-85	-14	-180	-43	-343	-115	2.5	60	400
107	2	23	2	2	2	9	5	4	5	8	4	5	6	6	5	6	6	1800	1900	1850	1750	1850	1800	3000	10000	5000	2000	5500	4000	25	40	30	100	200	150	510	225	1,890	425	28	14	-28	-22	-95	-60	-1,890	-425	1	20	200
108	2	23	2	2	3	6	2	5	6	8	4	4	8	8	6	5	8	1800	1900	1860	1800	1900	1820	12	300	150	1000	6000	2000	10	300	60	60	300	180	688	395	785	280	130	140	-63	-30	-420	-43	-785	-175	2	10	200
109	2	24	4	1	4	8	3	1	5	7	3	3	6	7	4	5	6	1845	1875	1860	1700	1820	1780	65	135	100	70	130	95	20	45	30	50	85	60	600	310	1,890	378	240	218	-28	-22	-95	-60	-343	-115	2	35	550
110	2	24	3	1	1	8	2	4	5	8	2	3	4	6	2	2	4	1800	1850	1825	1800	1850	1825	25	100	60	1000	2200	1500	10	20	15	20	45	35	510	268	1,890	475	43	22	-28	-14	-95	-60	-1,890	-378	2	20	200
111	2	24	6	1	1	6	3	1	9	6	4	2	8	8	6	5	8	1575	1900	1670	1450	1850	1500	3	1000	75	250	17500	800	5	40	20	20	150	130	335	225	1,890	378	28	14	-28	-70	-688	-458	-1,890	-475	10	70	700
112	2	24	7	1	1	6	2	4	5	5	2	2	6	4	3	3	5	1750	1850	1800	1600	1800	1700	100	2000	1000	1000	4000	3000	40	100	60	55	100	60	420	185	1,890	330	108	43	-28	-14	-65	-20	-1,005	-115	1	10	100
113	2	24	4	1	3	3	5	1	6	7	3	3	5	7	4	5	7	1780	1810	1790	1500	1700	1650	15	70	30	3000	20000	5000	40	70	50	10	100	40	510	268	1,890	378	108	43	-63	-14	-180	-43	-1,450	-330	1	20	200
114	2	24	7	1	4	4	2	3	5	9	4	5	7	8	4	5	7	1850	1930	1875	1750	1875	1850	5000	15000	10000	75000	125000	100000	15	25	20	40	80	60	510	268	1,890	475	43	22	-28	-14	-65	-30	-785	-280	1	10	200
115	2	24	7	1	3	5	3	5	5	8	5	3	8	8	6	6	7	1820	1870	1850	1820	1870	1850	45	55	50	199	300	200	90	150	120	90	150	120	510	268	1,890	475	43	14	-63	-14	-510	-268	-1,890	-475	1	10	100
116	2	24	2	2	1	8	3	4	6	6	1	2	4	7	4	4	6	1800	1900	1860	1800	1900	1890	10	200	90	500	3000	1000	15	40	25	30	90	50	420	105	1,228	115	43	58	-158	-130	-510	-185	-1,670	-330	5	50	400
117	2	25	4	1	3	6	1	1	4	5	1	1	4	6	4	2	6	1700	1950	1850	1400	1900	1850	20	140	100	1800	5000	2000	28	45	35	50	80	70	335	145	1,670	378	43	43	-43	-58	-420	-145	-1,890	-425	1	10	150
118	2	25	7	1	3	4	1	1	4	7	2	3	5	7	4	5	5	1800	2000	1950	1800	1950	1900	100	10000	3500	500	3500	1200	8	25	12	30	120	60	600	268	1,890	378	85	88	-28	-14	-95	-60	-785	-280	2	50	500
119	2	25	2	2	1	4	2	4	7	5	3	4	7	7	5	6	5	1200	1600	1500	1200	1600	1400	400	2000	1500	30000	80000	50000	30	75	45	50	80	60	420	145	1,228	330	28	14	-63	-43	-420	-60	-1,005	-280	1	10	200
120	2	26	6	1	1	7	4	3	10	9	4	4	9	7	5	4	8	1750	1800	1765	1900	1950	1922	20	30	25	100	200	180	30	40	35	60	120	90	510	268	1,890	378	108	58	-28	-14	-420	-225	-1,890	-378	3	30	300
121	2	26	7	1	2	5	2	3	7	6	1	1	5	6	3	3	6	1700	1900	1800	1700	1900	1800	250	1000	500	50	150	100	15	35	20	40	100	70	180	185	1,670	378	43	22	-63	-22	-180	-105	-565	-175	1	10	1,000
122	2	27	6	1	3	7	5	4	9	6	3	3	6	5	5	5	6	1750	1850	1790	1300	1700	1600	30	100000	1000	300	3000	1000	15	40	25	5	120	30	510	225	1,890	425	85	88	-28	-14	-420	-43	-1,890	-425	0	6	500
123	2	27	4	1	2	3	1	1	5	7	3	5	6	7	5	5	6	1750	1850	1800	1880	1940	1920	400	600	500	1800	2200	2000	15	30	25	25	35	30	775	268	1,890	425	28	22	-43	-22	-510	-225	-1,890	-378	2	20	200
124	2	28	7	1	2	6	3	2	8	7	4	3	7	5	2	2	6	1600	1880	1780	1780	1900	1850	20	8000	3000	100	1000	400	7	50	25	20	120	40	510	225	1,890	475	28	14	-63	-22	-180	-105	-1,890	-378	2	50	500
125	2	31	7	1	4	5	3	2	6	9	4	7	7	8	4	6	7	1875	1925	1900	1300	1600	1400	500	2000	1000	50	200	100	20	45	25	75	150	120	600	268	1,890	425	315	218	-28	-30	-65	-30	-785	-175	5	30	300
126	2	53	7	1	4	6	5	2	6	9	6	3	9	5	5	4	7	1750	1850	1800	1800	1850	1800	90	220	200	2500	3800	3000	25	40	30	40	60	45	510	268	1,670	378	160	43	-43	-14	-43	-20	-343	-115	3	20	300
AVRG	1.52	22.2	4.0	1.3	1.8	**5.4**	**2.3**	**2.8**	**5.6**	6.6	2.7	3.8	5.9	6.4	4.0	4.8	6.4	1708	1862	1799	1696	1868	1796	703	36,612	9,420	40,094	65,518	47,491	21	64	38	43	124	77	518.4	246.5	1,718.4	384.4	120.8	74.6	-63.0	-35.7	-267.4	-110.0	-1,381.7	-310.0	3.0	30.4	485.4
MEDIAN	2.0	22.0	4.0	1.0	1.0	**5.0**	**2.0**	**3.0**	**5.0**	7.0	2.5	4.0	6.0	6.0	4.0	5.0	6.0	1765	1890	1810	1780	1900	1850	20	140	80	240	1,000	600	15	45	30	30	85	50	510.0	267.5	1,890.0	377.5	107.5	57.5	-42.5	-21.5	-257.5	-68.8	-1,670.0	-330.0	2.0	20.0	300.0

Note: *In order to preserve participants' anonymity, results in Table A5 have been ranked in terms of gender and age.*

TABLE A.6 – Estimated variables from the Behavioral Tests (1/2)

	sex	age	studies	faculty	labour	E	P	m1	m2	m3	M_{med}	M_{avrg}	α^+	α^-	γ^+	γ^-	β_{med}	β_{avrg}
1	1	18	1	1	1	2	-7.0	0.72	0.01	1.07	0.72	0.60	1.08	0.27	0.53	0.31	1.5	1.6
2	1	18	1	1	3	4	-6.0				N/A	N/A	0.59	0.51	0.12	0.25	1.7	1.8
3	1	18	1	1	1	-6	-10.0	0.04	0.15	0.14	0.14	0.11	2.27	0.40	1.00	0.23	2.0	1.8
4	1	18	1	1	1	1	2.0	0.00	0.00	0.20	0.00	0.07	1.17	0.42	1.00	0.37	2.5	2.7
5	1	19	2	1	3	18	12.0	0.37	0.83	1.28	0.83	0.83	0.77	0.44	0.68	0.29	1.7	1.7
6	1	19	2	1	1	-2	-8.0	0.65	0.09	1.11	0.65	0.61	0.78	0.76	0.45	0.52	10.0	8.3
7	1	19	2	1	1	4	-2.0	0.02	0.02	0.19	0.02	0.08	0.63	0.27	0.27	0.36	1.8	2.1
8	1	19	4	1	1	0	1.0	0.07	0.01	0.77	0.07	0.28	1.30	0.34	0.69	0.45	2.0	3.0
9	1	19	3	1	1	2	-7.0	0.37	0.01	1.15	0.37	0.51	0.89	0.27	0.47	0.30	4.0	4.2
10	1	19	2	2	1	6	0.0	0.25	0.02	0.40	0.25	0.22	1.05	0.38	0.32	0.19	3.0	3.3
11	1	19	2	6	1	2	-4.0	0.21	0.37	0.62	0.37	0.40	0.90	0.64	0.72	0.55	3.0	3.7
12	1	19	2	6	1	1	-4.0	0.36	0.35	1.11	0.36	0.61	0.66	0.88	0.64	0.76	5.0	26.7
13	1	20	4	1	1	-1	-5.0	0.28	0.10	2.09	0.28	0.83	0.67	0.57	0.20	0.45	2.0	3.7
14	1	20	3	1	1	1	-4.0	0.00	0.10	0.28	0.10	0.12	2.08	0.44	1.00	0.88	1.0	1.2
15	1	20	3	1	1	1	-5.0	0.36	0.97	0.71	0.71	0.68	2.20	0.39	1.00	1.00	2.0	2.2
16	1	20	3	1	1	0	-3.0	0.23	0.03	0.32	0.23	0.19	1.02	0.47	0.70	0.37	1.0	1.0
17	1	20	1	2	1	0	-5.0	0.51	0.09	0.29	0.29	0.30	0.94	0.64	0.52	0.55	5.0	5.0
18	1	21	1	1	1	9	2.0	0.02	0.02	0.19	0.02	0.08	1.05	0.24	0.60	0.47	2.0	1.8
19	1	21	4	1	1	2	0.0	0.40	0.10	0.69	0.40	0.40	1.06	0.26	0.59	0.32	6.0	5.3
20	1	21	4	1	1	-2	-5.0	0.02	0.08	0.43	0.08	0.17	1.90	0.17	1.00	0.80	2.0	2.7
21	1	21	4	1	1	7	-3.0	0.08	0.07	0.26	0.08	0.14	1.76	1.00	1.00	0.74	2.5	3.2
22	1	21	4	1	1	-4	-6.0	1.04	0.40	0.41	0.41	0.62	1.53	0.33	0.87	0.86	3.0	7.0
23	1	21	4	1	1	6	-1.0	0.10	0.02	0.26	0.10	0.12	0.66	0.40	0.38	0.52	2.0	1.7
24	1	21	7	1	2	1	-1.0	0.07	0.02	0.13	0.07	0.07	1.10	0.30	0.58	0.15	1.5	2.2
25	1	21	7	1	2	6	-1.0	0.04	0.12	0.82	0.12	0.33	0.89	0.29	0.62	0.40	3.5	3.8
26	1	21	7	1	2	1	-6.0	0.11	0.12	0.04	0.11	0.09	0.86	0.36	0.32	0.27	2.0	3.0
27	1	21	1	2	3	7	1.0	0.73	0.02	0.35	0.35	0.37	0.60	0.61	0.47	1.00	5.0	4.7
28	1	22	1	1	3	8	0.0	0.75	0.83	0.40	0.75	0.66	1.03	0.51	0.67	0.84	4.0	3.7
29	1	22	3	1	4	-6	-7.0	0.40	0.09	1.29	0.40	0.59	1.19	0.39	0.41	0.51	3.0	3.7
30	1	22	4	1	2	4	1.0	0.21	0.03	0.72	0.21	0.32	0.71	0.58	0.29	0.26	3.0	5.0
31	1	22	4	1	2	3	3.0	0.94	0.03	0.85	0.85	0.61	1.73	0.75	0.72	0.43	5.0	5.8
32	1	22	6	1	3	-2	-10.0	0.33	0.06	0.23	0.23	0.21	0.66	0.38	0.33	0.19	4.0	4.3
33	1	22	7	1	2	3	-4.0	0.12	0.06	2.13	0.12	0.77	1.70	0.26	0.99	0.20	2.0	2.3
34	1	22	7	1	3	1	2.0	0.31	0.03	0.89	0.31	0.41	0.54	0.55	0.81	0.57	8.0	8.0
35	1	22	4	1	2	0	-12.0	0.78	0.02	0.65	0.65	0.48	0.88	0.33	0.45	0.12	1.5	1.3
36	1	22	7	1	2	13	-3.0	0.43	0.05	0.18	0.18	0.22	0.92	0.27	0.65	0.23	5.0	4.7
37	1	23	1	1	2	0	-6.0	1.41	0.43	1.91	1.41	1.25	0.97	0.64	0.60	0.37	2.0	4.3
38	1	23	1	1	3	3	-12.0	0.00	0.02	0.73	0.02	0.25	1.42	0.42	0.86	0.34	1.2	1.1
39	1	23	4	1	4	-1	-2.0	0.37	0.02	0.36	0.36	0.25	1.17	0.34	1.00	0.52	5.0	9.0
40	1	23	7	1	2	1	-5.0	0.08	0.04	0.47	0.08	0.20	0.57	0.41	0.47	0.78	2.0	2.8
41	1	23	4	1	2	2	5.0	0.44	0.03	0.53	0.44	0.33	0.36	0.88	0.81	0.76	2.0	1.7
42	1	23	7	1	2	1	-6.0	0.32	0.09	1.94	0.32	0.79	0.99	0.31	0.50	0.20	5.0	6.7
43	1	23	7	1	3	-5	-5.0	0.15	0.01	0.28	0.15	0.15	0.79	0.64	0.05	0.25	5.0	5.0
44	1	23	4	1	1	6	-5.0	0.21	0.17	2.44	0.21	0.94	0.52	0.81	0.13	0.74	4.0	4.3
45	1	23	4	1	2	1	-5.0	0.17	0.78	0.23	0.23	0.39	0.74	0.37	0.73	0.49	2.0	2.2
46	1	23	6	1	2	5	0.0	0.53	0.01	0.57	0.53	0.37	1.05	0.24	1.00	1.00	0.9	0.7
47	1	23	4	1	1	5	-1.0	0.23	0.02	0.96	0.23	0.40	0.91	0.47	0.42	0.55	2.0	2.0
48	1	23	7	1	2	10	3.0	0.16	0.03	0.98	0.16	0.39	1.14	0.55	0.69	0.50	1.8	1.7
49	1	23	7	1	3	2	-7.0	0.07	0.01	0.89	0.07	0.32	0.73	0.68	0.75	0.45	5.0	5.0
50	1	24	4	1	1	7	-1.0	0.34	0.25	2.98	0.34	1.19	2.04	0.34	1.00	0.05	2.0	2.3
51	1	24	6	1	1	2	-3.0	0.14	0.05	1.57	0.14	0.58	1.12	1.25	0.43	0.93	3.0	3.7
52	1	24	7	1	1	2	-3.0	0.52	0.01	0.44	0.44	0.32	0.79	0.35	0.62	0.47	2.0	1.8
53	1	24	7	1	2	7	-2.0	0.07	0.14	0.16	0.14	0.12	1.81	0.30	1.00	0.14	10.0	21.7
54	1	24	7	3	2	6	0.0	0.15	0.01	0.55	0.15	0.24	1.06	0.79	0.27	0.82	4.0	5.0
55	1	24	7	1	2	-1	-7.0	0.28	0.01	0.87	0.28	0.39	0.46	0.32	0.22	0.76	2.5	2.8
56	1	25	3	1	2	-1	-8.0	0.32	0.47	0.38	0.38	0.39	0.95	0.37	0.61	0.10	1.0	1.0
57	1	25	7	1	2	-4	-14.0	0.17	0.02	0.77	0.17	0.32	2.67	0.27	1.00	0.18	5.0	6.0
58	1	26	7	1	3	7	-5.0	0.35	0.52	0.20	0.35	0.36	2.55	0.33	1.00	0.13	2.5	2.5
59	1	27	7	1	3	2	-6.0	0.17	0.07	0.89	0.17	0.38	0.92	0.27	0.66	0.67	2.0	2.7
60	1	28	4	1	4	5	-6.0	0.19	0.07	1.34	0.19	0.53	2.10	0.40	1.00	0.18	5.0	5.8
61	2	17	1	1	1	16	2.0	0.26	0.33	0.59	0.33	0.39	0.63	0.54	0.61	0.26	5.0	19.0
62	2	18	1	1	1	0	-3.0	0.21	0.02	0.35	0.21	0.19	0.74	0.66	0.59	0.63	2.0	2.3
63	2	18	1	1	1	-2	-7.0	0.20	0.05	0.86	0.20	0.37	1.66	0.31	1.00	0.62	3.0	2.7
64	2	18	1	1	1	-3	-7.0	0.10	0.19	1.35	0.19	0.54	2.46	0.67	1.00	0.25	4.0	4.2
65	2	18	1	1	3	4	-3.0	0.04	0.14	0.77	0.14	0.32	0.72	0.49	0.41	0.17	2.5	2.3
66	2	18	1	1	1	6	-1.0	0.31	0.17	2.27	0.31	0.92	0.62	0.48	0.43	0.27	1.5	1.4
67	2	18	2	1	1	12	1.0	0.03	0.07	0.19	0.07	0.10	1.04	0.23	1.00	0.85	1.0	1.0
68	2	18	2	2	1	3	-1.0	0.29	0.14	1.07	0.29	0.50	0.74	0.08	0.74	0.86	1.0	1.3
69	2	19	2	2	1	1	-3.0	0.18	0.03	0.42	0.18	0.21	0.76	0.45	0.61	0.88	2.0	2.4
70	2	19	2	2	1	0	-9.0	0.54	0.01	1.03	0.54	0.52	0.81	0.45	0.54	0.47	2.5	2.5

TABLE A.6 – Estimated variables from the Behavioral Tests (2/2)

	sex	age	studies	faculty	labour	E	P	m1	m2	m3	M_{med}	M_{avrg}	α^+	α^-	γ^+	γ^-	β_{med}	β_{avrg}
71	2	19	1	2	3	6	0.0	0.64	0.30	0.54	0.54	0.49	0.96	0.05	0.59	1.00	2.0	1.8
72	2	19	2	2	1	0	-8.0	0.31	0.58	3.25	0.58	1.38	0.85	0.06	0.68	1.00	1.5	2.7
73	2	20	1	1	2	20	6.0	0.03	0.17	0.47	0.17	0.23	0.42	2.29	0.77	1.00	4.0	4.7
74	2	20	2	1	1	5	6.0	0.23	0.20	0.62	0.23	0.35	0.89	0.65	0.76	0.65	5.0	4.0
75	2	20	2	1	1	1	-4.0	0.19	0.34	0.64	0.34	0.39	1.06	0.19	0.94	0.38	2.0	2.0
76	2	20	2	1	1	-3	-3.0	0.07	0.01	0.47	0.07	0.18	0.93	0.48	0.98	0.40	2.5	2.4
77	2	20	2	2	1	3	-5.0	0.08	0.02	1.55	0.08	0.55	0.93	0.75	0.37	0.54	3.5	3.7
78	2	20	2	2	1	5	-1.0	0.40	0.27	0.56	0.40	0.41	1.26	0.56	0.53	0.32	3.5	3.7
79	2	21	4	1	1	4	1.0	0.91	0.06	0.66	0.66	0.54	1.00	0.75	0.55	0.42	4.0	4.7
80	2	21	4	1	3	3	-3.0	0.38	0.08	0.77	0.38	0.41	2.01	0.54	1.00	0.81	1.1	1.0
81	2	21	7	1	2	2	2.0	0.33	0.37	1.80	0.37	0.83	0.75	0.49	0.97	1.00	2.0	2.3
82	2	21	4	1	3	3	-7.0	0.52	0.20	0.43	0.43	0.38	1.01	0.32	0.70	0.50	1.0	1.0
83	2	21	4	1	1	3	1.0	0.47	0.12	0.86	0.47	0.48	0.49	1.12	0.72	0.77	5.0	4.0
84	2	21	2	2	1	2	-4.0	0.63	0.02	0.54	0.54	0.40	0.79	0.40	0.38	0.37	3.0	3.3
85	2	21	2	2	1	10	2.0	0.21	0.01	0.70	0.21	0.31	0.99	0.81	0.38	0.75	3.5	3.8
86	2	21	2	2	4	6	0.0	0.41	0.02	0.26	0.26	0.23	0.72	0.38	0.63	0.69	1.0	1.0
87	2	22	1	1	4	4	-4.0	0.12	0.05	0.50	0.12	0.23	1.17	1.05	0.64	0.64	2.0	2.2
88	2	22	4	1	1	-1	-6.0	0.36	0.10	1.71	0.36	0.72	1.00	0.64	0.73	0.64	4.0	3.7
89	2	22	4	1	3	1	0.0	0.29	0.04	0.80	0.29	0.37	1.05	0.39	0.49	0.24	5.0	4.7
90	2	22	4	1	4	13	13.0	1.34	0.16	0.36	0.36	0.62	1.60	0.56	1.00	0.58	1.5	1.3
91	2	22	5	1	1	2	-4.0	0.36	1.00	0.23	0.36	0.53	0.78	0.62	0.62	0.44	5.0	5.0
92	2	22	4	1	1	0	-1.0	0.62	0.33	0.92	0.62	0.62	1.15	0.27	0.68	1.00	4.0	3.7
93	2	22	4	1	1	7	6.0	0.51	0.34	0.56	0.51	0.47	0.94	0.99	0.62	0.77	1.0	1.0
94	2	22	4	1	1	1	-7.0	0.51	0.85	2.16	0.85	1.17	0.67	0.35	1.00	0.95	5.0	6.0
95	2	22	7	1	2	2	-7.0	2.88	0.03	1.12	1.12	1.34	0.85	0.94	0.67	0.89	0.9	0.9
96	2	22	7	1	1	1	-2.0	0.24	0.12	0.38	0.24	0.25	0.24	0.53	0.16	0.11	2.0	1.8
97	2	22	7	1	1	1	-1.0	0.01	0.38	1.64	0.38	0.68	0.24	1.08	0.16	0.62	10.0	10.5
98	2	22	3	1	1	6	3.0	0.05	0.11	0.25	0.11	0.14	0.72	0.69	0.15	0.35	1.0	1.0
99	2	22	2	2	1	0	-8.0	0.40	0.34	0.95	0.40	0.57	0.96	0.73	0.60	0.44	1.5	1.5
100	2	23	7	1	2	4	0.0	0.42	0.21	0.88	0.42	0.51	1.06	1.04	0.93	1.00	5.0	5.7
101	2	23	7	1	1	7	2.0	0.20	0.20	1.40	0.20	0.60	1.08	0.34	0.62	0.66	1.4	1.4
102	2	23	4	1	3	-3	-12.0	1.43	0.01	0.99	0.99	0.81	0.84	0.54	0.63	0.82	1.5	1.7
103	2	23	4	1	1	6	1.0	0.30	0.12	0.19	0.19	0.20	0.67	0.40	1.00	0.39	1.0	1.0
104	2	23	7	1	1	12	4.0	1.36	0.15	0.28	0.28	0.60	0.76	0.48	0.32	0.12	2.0	1.8
105	2	23	7	1	2	-1	-3.0	0.46	2.57	0.45	0.46	1.16	0.92	0.99	0.66	0.76	10.0	10.0
106	2	23	7	1	1	1	1.0	0.12	0.39	0.73	0.39	0.41	1.27	0.33	0.71	0.08	4.0	4.2
107	2	23	2	2	2	0	-7.0	0.33	0.51	0.42	0.42	0.42	0.89	0.31	0.76	0.98	2.0	1.7
108	2	23	2	2	3	5	-6.0	0.25	0.63	0.66	0.63	0.51	0.86	0.44	0.16	0.16	2.0	1.7
109	2	24	4	1	4	2	-4.0	0.10	0.01	1.20	0.10	0.44	1.23	0.30	0.53	0.10	3.5	3.7
110	2	24	3	1	1	-2	0.0	0.22	0.31	0.38	0.31	0.30	1.05	0.31	0.99	0.86	2.0	2.0
111	2	24	6	1	1	1	-10.0	0.32	0.27	0.62	0.32	0.40	0.71	1.82	0.64	1.00	7.0	8.0
112	2	24	7	1	1	-2	-1.0	0.36	1.13	0.50	0.50	0.66	0.72	0.09	0.51	0.67	1.0	1.0
113	2	24	4	1	3	3	-4.0	0.12	0.46	0.54	0.46	0.37	0.96	0.36	0.60	0.56	2.0	1.7
114	2	24	7	1	4	11	3.0	0.18	0.21	1.45	0.21	0.61	1.05	0.30	0.99	0.35	1.0	1.3
115	2	24	7	1	3	6	-5.0	0.18	0.01	0.23	0.18	0.14	1.05	1.06	1.00	0.95	1.0	1.0
116	2	24	2	2	1	-8	-13.0	0.17	0.35	3.62	0.35	1.38	0.48	0.79	0.19	0.39	5.0	4.7
117	2	25	4	1	3	-1	-3.0	0.58	0.28	0.49	0.49	0.45	0.60	0.67	0.56	0.75	1.0	1.2
118	2	25	7	1	3	7	2.0	0.27	0.48	0.64	0.48	0.46	1.04	0.35	0.63	0.31	5.0	4.0
119	2	25	2	2	1	2	-5.0	0.30	0.31	0.88	0.31	0.50	0.59	0.50	0.34	0.25	1.0	1.3
120	2	26	6	1	1	2	-6.0	0.18	0.01	0.35	0.18	0.18	0.96	0.77	0.60	0.63	3.0	3.0
121	2	26	7	1	2	-4	-6.0	0.89	0.02	1.20	0.89	0.70	0.54	0.39	0.58	0.13	1.0	4.0
122	2	27	6	1	3	-7	-12.0	0.31	0.28	1.52	0.31	0.70	0.92	0.51	0.68	0.84	0.6	1.9
123	2	27	4	1	2	11	4.0	0.25	0.12	0.23	0.23	0.20	1.39	0.85	1.00	0.63	2.0	2.0
124	2	28	7	1	2	2	3.0	1.50	0.18	2.25	1.50	1.31	0.94	0.42	0.98	0.77	5.0	4.0
125	2	31	7	1	4	11	2.0	0.11	0.03	0.47	0.11	0.20	1.27	0.27	0.53	0.30	3.0	3.7
126	2	53	7	1	4	8	3.0	0.18	0.27	0.48	0.27	0.31	0.93	0.25	0.48	0.15	3.0	2.7
						2.9	**-2.7**	94.4%	97.6%	74.4%	**% overpr**	AVRG	**1.02**	**0.52**	**0.64**	**0.53**	**3.01**	**3.64**
												MEDIAN	**0.93**	**0.44**	**0.63**	**0.50**	**2.00**	**2.67**
											avrg	**n=126**	**0.91**	**0.50**	**0.52**	**0.40**	**3.0**	**3.51**
											median	**n=126**	**0.96**	**0.43**	**0.60**	**0.58**	**2.0**	**2.33**

Note: *In order to preserve participants' anonymity, results in Table A6 have been ranked in terms of gender and age.*

TABLE A.7 – Histograms of behavioral variables (1/2)

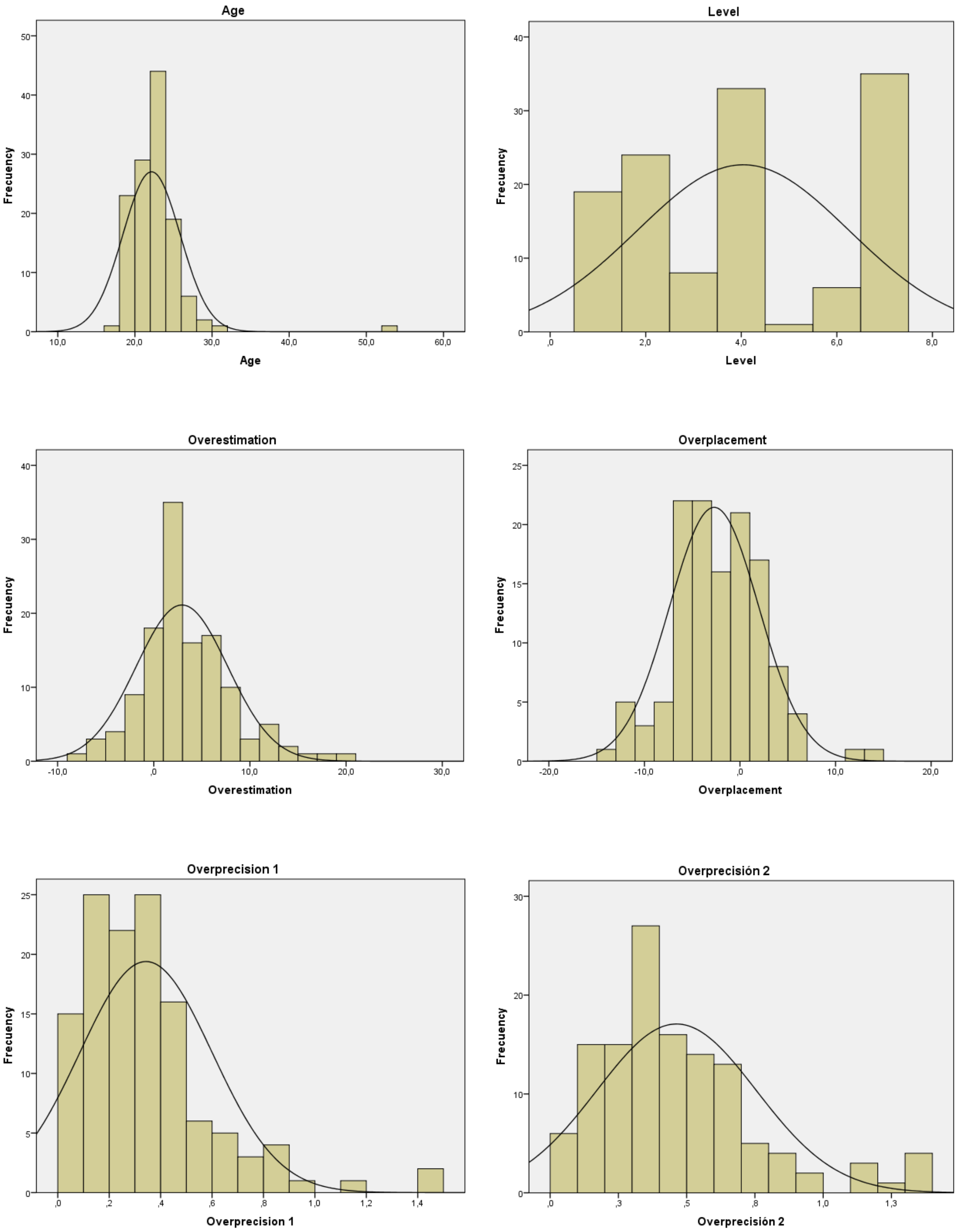
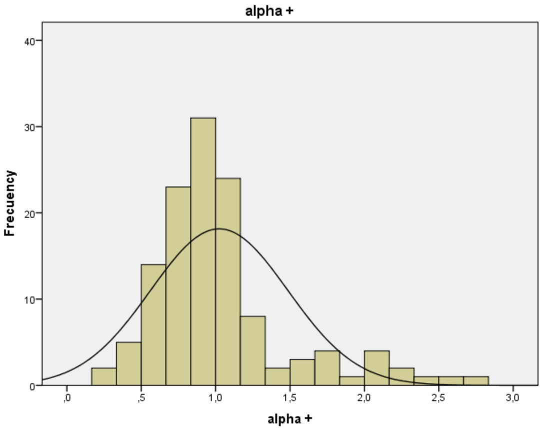
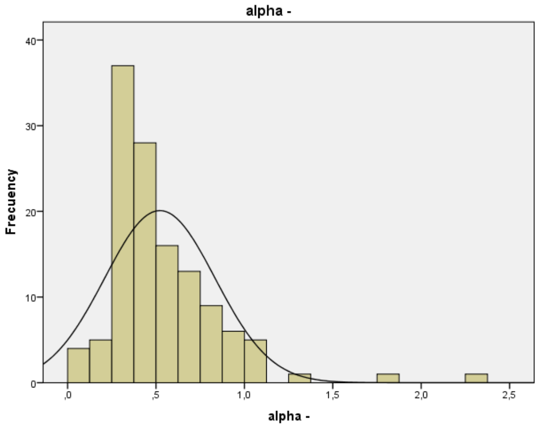
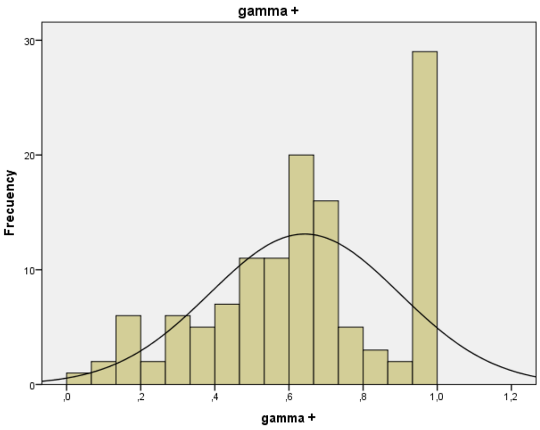
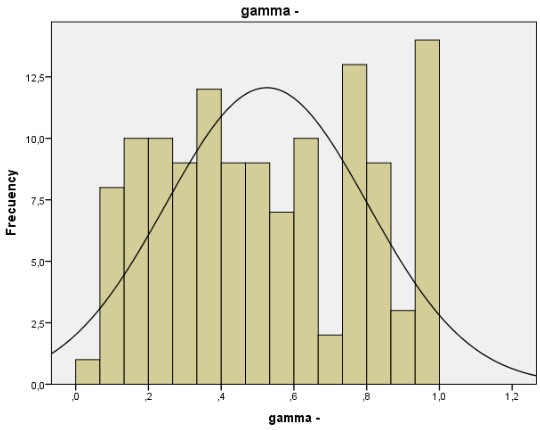


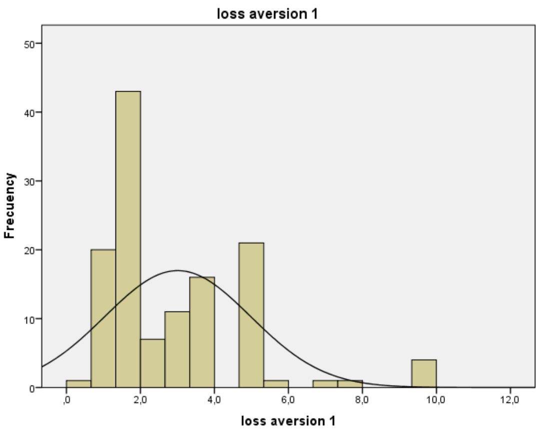
TABLE A.7 – Histograms of behavioral variables (2/2)











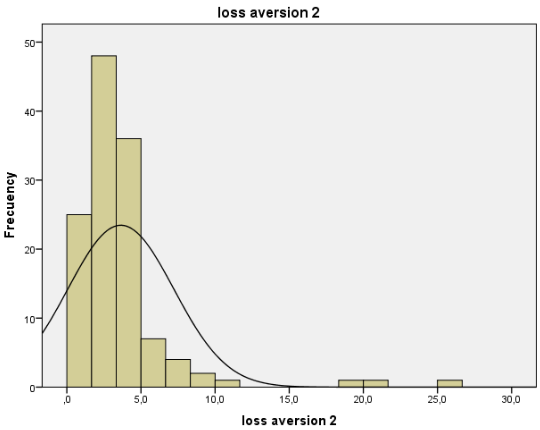
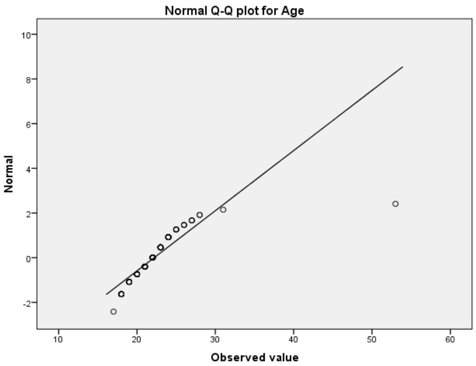
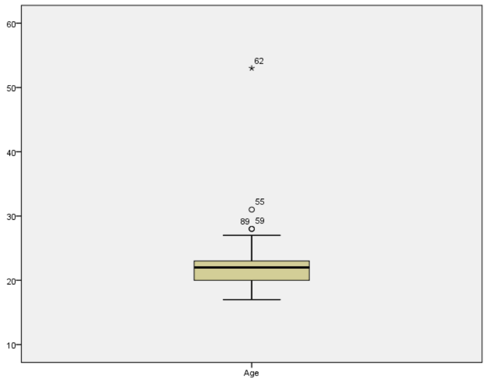
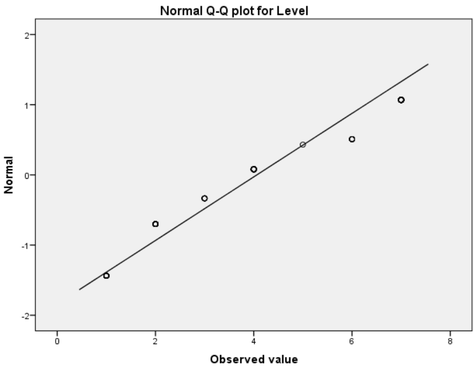
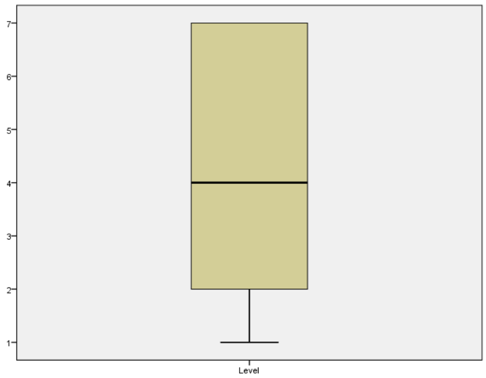


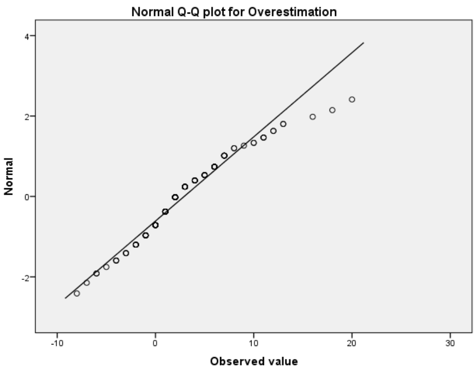
TABLE A.8 – Normal Q-Q and Box-and-whiskers plots of behavioral variables (1/3)

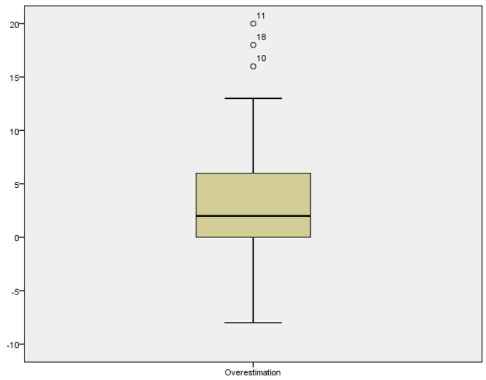


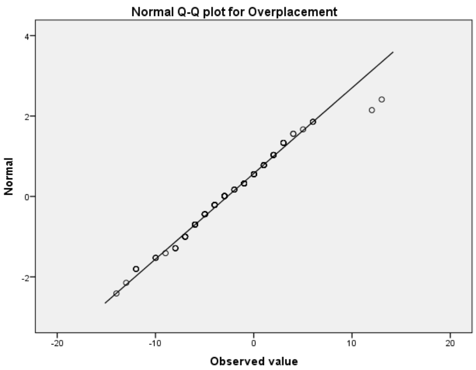












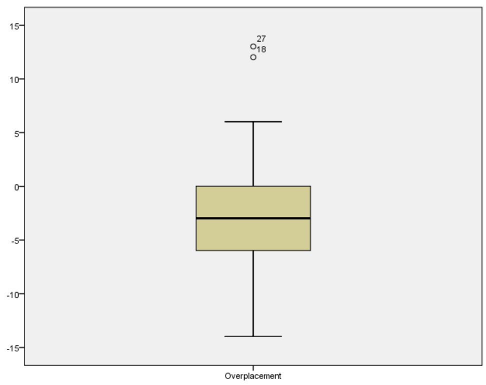
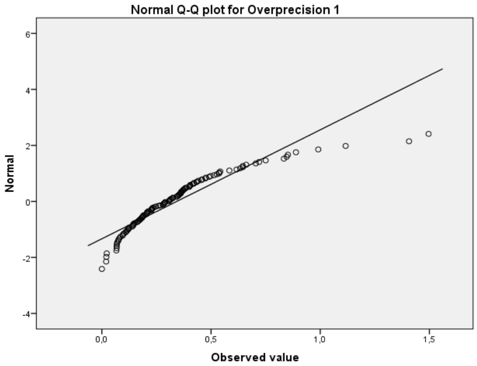
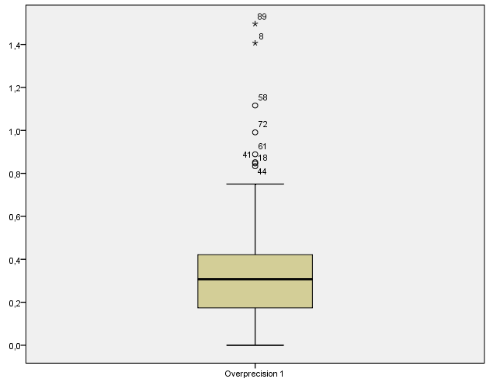
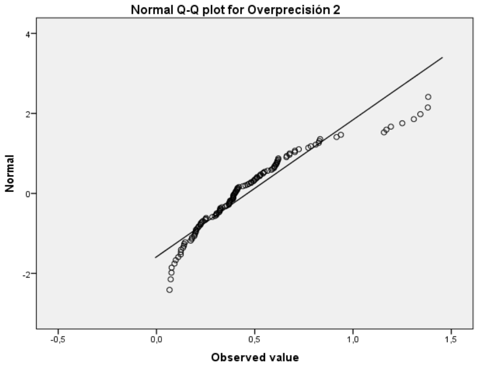
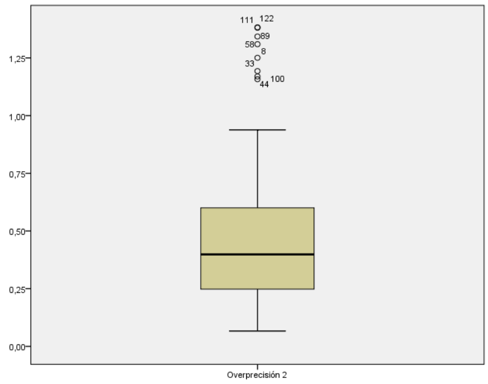


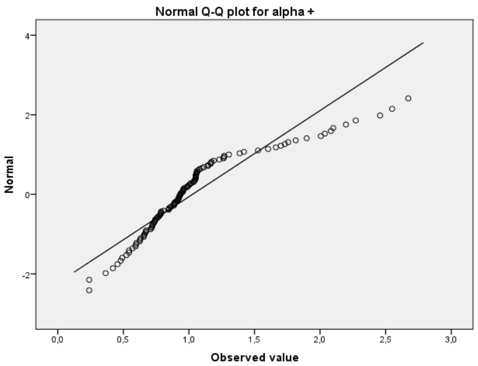
TABLE A.8 – Normal Q-Q and Box-and-whiskers plots of behavioral variables (2/3)

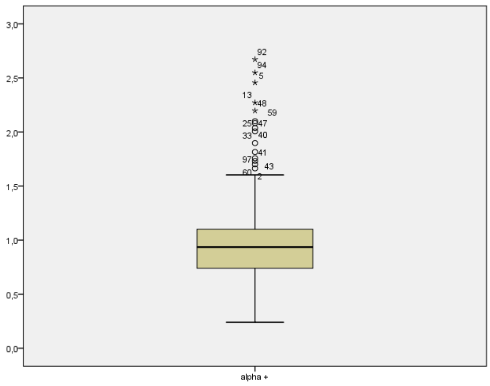


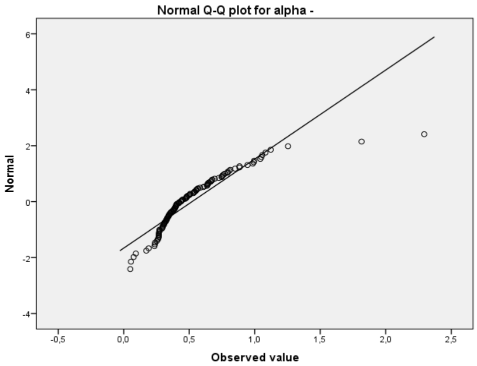












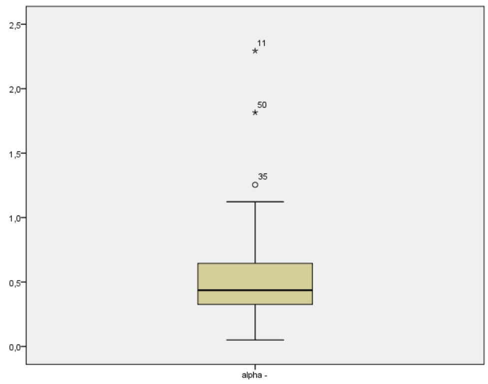
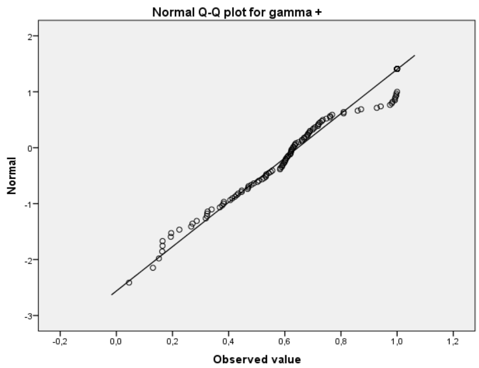
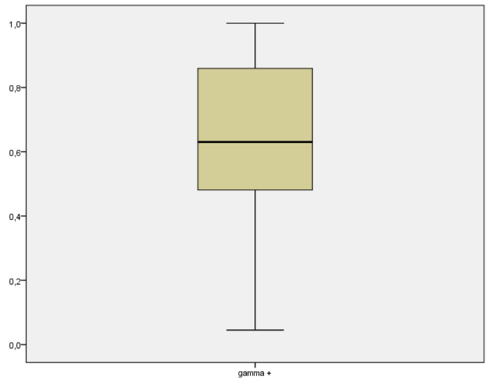
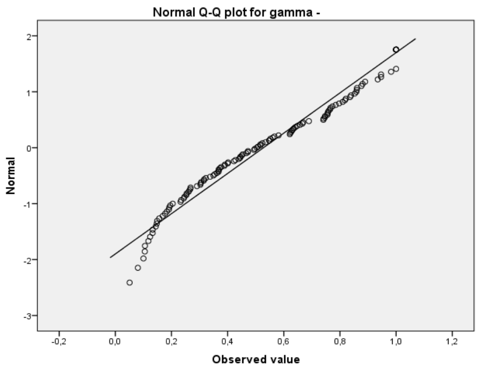
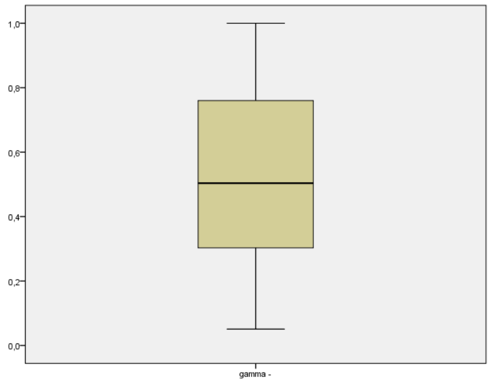


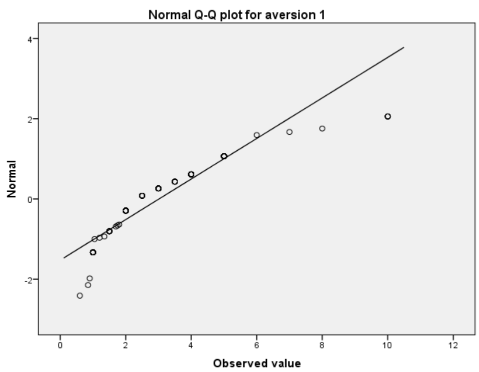
TABLE A.8 – Normal Q-Q and Box-and-whiskers plots of behavioral variables (3/3)

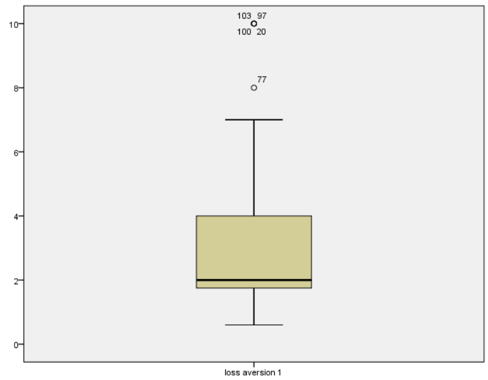


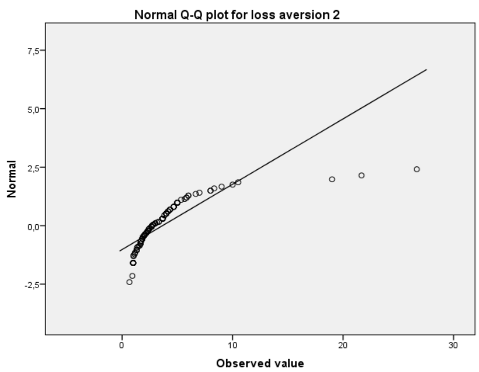












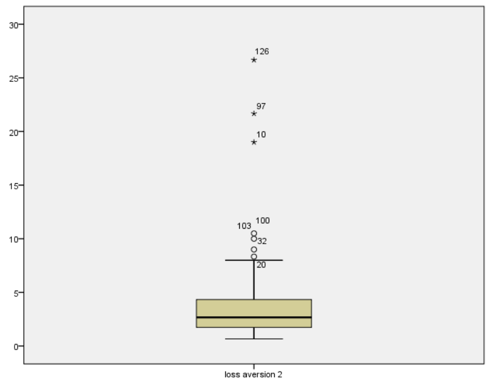


TABLE A.9 – ANOVA tests for Gender and Skills

ANOVA Gender

		Squares	df	Square	F	Sig.
E	Between Groups	17.894	1	17.894	.789	.376
	Within Groups	2812.464	124	22.681		
	Total	2830.357	125			
P	Between Groups	56.638	1	56.638	2.613	.109
	Within Groups	2688.188	124	21.679		
	Total	2744.825	125			
Mmed	Between Groups	.195	1	.195	2.992	.086
	Within Groups	8.003	123	.065		
	Total	8.198	124			
Mavg	Between Groups	.362	1	.362	4.367	.039
	Within Groups	10.208	123	.083		
	Total	10.570	124			
alpha +	Between Groups	1.218	1	1.218	5.941	.016
	Within Groups	25.420	124	.205		
	Total	26.638	125			
alpha -	Between Groups	.390	1	.390	4.086	.045
	Within Groups	11.834	124	.095		
	Total	12.224	125			
gamma +	Between Groups	.014	1	.014	.215	.644
	Within Groups	8.154	124	.066		
	Total	8.168	125			
gamma -	Between Groups	.375	1	.375	5.008	.027
	Within Groups	9.277	124	.075		
	Total	9.651	125			
βmed	Between Groups	3.538	1	3.538	.907	.343
	Within Groups	483.529	124	3.899		
	Total	487.067	125			
βavg (r)	Between Groups	9.601	1	9.601	2.487	.117
	Within Groups	467.206	121	3.861		
	Total	476.806	122			

Descriptives

Gender		Mean	Std. Error
E	Female	2.533	.5622
	Male	3.288	.6283
P	Female	-3.410	.5711
	Male	-2.067	.5979
Mmed	Female	0.301	.0334
	Male	0.380	.0313
Mavg	Female	0.406	.0346
	Male	0.514	.0377
alpha +	Female	1.127	.0698
	Male	0.930	.0436
alpha -	Female	0.463	.0276
	Male	0.575	.0461
gamma +	Female	0.631	.0352
	Male	0.652	.0296
gamma -	Female	0.468	.0336
	Male	0.577	.0351
βmed	Female	3.183	.2551
	Male	2.847	.2429
βavg (r)	Female	3.477	.2546
	Male	2.917	.2466

ANOVA Skills

		Squares	df	Square	F	Sig.
E	Between Groups	1.709	1	1.709	.075	.785
	Within Groups	2828.648	124	22.812		
	Total	2830.357	125			
P	Between Groups	28.971	1	28.971	1.323	.252
	Within Groups	2715.854	124	21.902		
	Total	2744.825	125			
Mmed	Between Groups	.001	1	.001	.018	.894
	Within Groups	8.196	123	.067		
	Total	8.198	124			
Mavg	Between Groups	.017	1	.017	.197	.658
	Within Groups	10.553	123	.086		
	Total	10.570	124			
alpha +	Between Groups	0.802	1	.802	3.848	.052
	Within Groups	25.837	124	.208		
	Total	26.638	125			
alpha -	Between Groups	0.013	1	.013	.136	.713
	Within Groups	12.211	124	.098		
	Total	12.224	125			
gamma +	Between Groups	.507	1	.507	8.198	.005
	Within Groups	7.662	124	.062		
	Total	8.168	125			
gamma -	Between Groups	.145	1	.145	1.897	.171
	Within Groups	9.506	124	.077		
	Total	9.651	125			
βmed	Between Groups	.073	1	.073	.018	.892
	Within Groups	486.994	124	3.927		
	Total	487.067	125			
βavg (r)	Between Groups	0.660	1	0.660	.168	.683
	Within Groups	476.147	121	3.935		
	Total	476.806	122			

Descriptives

Skills		Mean	Std. Error
E	Others	3.182	.9132
	Economics & Business	2.875	.4776
P	Others	-3.749	.8029
	Economics & Business	-2.486	.4751
Mmed	Others	0.350	.0318
	Economics & Business	0.342	.0271
Mavg	Others	0.488	.0672
	Economics & Business	0.457	.0284
alpha +	Others	0.850	.0379
	Economics & Business	1.060	.0485
alpha -	Others	0.499	.0531
	Economics & Business	0.526	.0319
gamma +	Others	0.504	.0378
	Economics & Business	0.671	.0256
gamma -	Others	0.599	.0610
	Economics & Business	0.510	.0270
βmed	Others	2.955	.3031
	Economics & Business	3.018	.2037
βavg (r)	Others	3.020	.2928
	Economics & Business	3.214	.2067

TABLE A.10 – Regression models. Behavioral biases to priors (1/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Gender		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: Overprecisión 2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.185[a]	.034	.026	.288

a. Predictors: (Constant), Gender

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.362	1	.362	4.367	.039[b]
	Residual	10.208	123	.083		
	Total	10.570	124			

a. Dependent Variable: Overprecisión 2

b. Predictors: (Constant), Gender

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.406	.037		10.882	.000
	Gender	.108	.052	.185	2.090	.039

a. Dependent Variable: Overprecisión 2

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Age (r)	.021[b]	0.238	.812	.022	.990
	Level	.054[b]	.612	.542	.055	.995
	Experience	-.013[b]	-.148	.882	-.013	.979
	Skills	-.057[b]	-.640	.523	-.058	1.000

a. Dependent Variable: Overprecisión 2

b. Predictors in the Model: (Constant), Gender

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
2	Gender		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: alpha +

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	.214[a]	.046	.038	.453

a. Predictors: (Constant), Gender

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	1.218	1	1.218	5.941	.016[b]
	Residual	25.420	124	.205		
	Total	26.638	125			

a. Dependent Variable: alpha +

b. Predictors: (Constant), Gender

Coefficients[a]

Model		(Constant)		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	1.127	.058		19.277	.000
	Gender	-.197	.081	-.214	-2.437	.016

a. Dependent Variable: alpha +

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
2	Age (r)	.055[b]	.620	.537	.056	.990
	Level	-.016[b]	-.185	.854	-.017	.995
	Experience	.145[b]	1.652	.101	.147	.979
	Skills	.073[b]	.832	.407	.075	1.000

a. Dependent Variable: alpha +

b. Predictors in the Model: (Constant), Gender

TABLE A.10 – Regression models. Behavioral biases to priors (2/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
3	Gender		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: alpha -

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	.179[a]	.032	.024	.309

a. Predictors: (Constant), Gender

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
3	Regression	.390	1	.390	4.086	.045b
	Residual	11.834	124	.095		
	Total	12.224	125			

a. Dependent Variable: alpha -

b. Predictors: (Constant), Gender

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
3	(Constant)	.463	.040		11.618	.000
	Gender	.111	.055	.179	2.021	.045

a. Dependent Variable: alpha -

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
3	Age (r)	-.054[b]	-.604	.547	-.054	.990
	Level	-.017[b]	-.190	.850	-.017	.995
	Experience	.060[b]	.674	.502	.061	.979
	Skills	-.091[b]	-1.034	.303	-.093	1.000

a. Dependent Variable: alpha -

b. Predictors in the Model: (Constant), Gender

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
4	Skills		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: gamma +

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	.249[a]	.062	.054	.249

a. Predictors: (Constant), Skills

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
4	Regression	.507	1	.507	8.198	.005b
	Residual	7.662	124	.062		
	Total	8.168	125			

a. Dependent Variable: gamma +

b. Predictors: (Constant), Skills

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
4	(Constant)	.504	.053		9.516	.000
	Skills	.167	.058	.249	2.863	.005

a. Dependent Variable: gamma +

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
4	Gender	.079[b]	.903	.368	.081	.979
	Age (r)	-.047[b]	-.532	.595	-.048	.973
	Level	-.082[b]	-.878	.382	-.079	.872
	Experience	.021[b]	.239	.811	.022	.982

a. Dependent Variable: gamma +

b. Predictors in the Model: (Constant), Skills

TABLE A.10 – Regression models. Behavioral biases to priors (3/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
5	Gender		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: gamma -

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
5	.197[a]	.039	.031	.274

a. Predictors: (Constant), Gender

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
5	Regression	.375	1	.375	5.008	.027[b]
	Residual	9.277	124	.075		
	Total	9.651	125			

a. Dependent Variable: gamma -

b. Predictors: (Constant), Gender

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
5	(Constant)	.468	.035		13.261	.000
	Gender	.109	.049	.197	2.238	.027

a. Dependent Variable: gamma -

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
5	Age (r)	-.135[b]	-1.534	.128	-.137	.990
	Level	-.040[b]	-.454	.651	-.041	.995
	Experience	-.096[b]	-1.081	.282	-.097	.979
	Skills	-.101[b]	-1.154	.251	-.103	1.000

a. Dependent Variable: gamma -

b. Predictors in the Model: (Constant), Gender

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
6	Level		Stepwise (Criteria: Probab.-of-F-to-enter <= ,050, Probab.-of-F-to-remove >= ,100).

a. Dependent Variable: Loss aversion 2 (r)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
6	.209[a]	.044	.036	1.941

a. Predictors: (Constant), Level

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
6	Regression	20.833	1	20.833	5.528	.020[b]
	Residual	455.973	121	3.768		
	Total	476.806	122			

a. Dependent Variable: Loss aversion 2 (r)

b. Predictors: (Constant), Level

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
6	(Constant)	2.429	.365		6.656	.000
	Level	.186	.079	.209	2.351	.020

a. Dependent Variable: Loss aversion 2 (r)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
6	Gender	-.128[b]	-1.443	.152	-.131	.995
	Age (r)	-.083[b]	-.808	.421	-.074	.753
	Experience	-.043[b]	-.453	.651	-.041	.872
	Skills	-.048[b]	-.529	.598	-.048	.956

a. Dependent Variable: Loss aversion 2 (r)

b. Predictors in the Model: (Constant), Level

TABLE A.11 – ANOVA tests for Gender and Skills on Factors

ANOVA Gender

		Sum of Squares	df	Mean Square	F	Sig.
OC	Between Groups	1.207	1	1.207	1.209	.274
	Within Groups	122.793	123	.998		
	Total	124.000	124			
Gains	Between Groups	1.442	1	1.442	1.448	.231
	Within Groups	123.558	124	.996		
	Total	125.000	125			
Losses	Between Groups	9.153	1	9.153	9.798	.002
	Within Groups	115.847	124	.934		
	Total	125.000	125			
Loss aversion	Between Groups	.415	1	.415	.413	.521
	Within Groups	124.585	124	1.005		
	Total	125.000	125			

Descriptives

		Mean	Std. Error
OC	Female	-.104	.117
	Male	.093	.133
Gains	Female	.112	.149
	Male	-.102	.103
Losses	Female	-.283	.113
	Male	.257	.128
Loss aversion	Female	.060	.118
	Male	-.055	.132

ANOVA Skills

		Squares	df	Square	F	Sig.
OC	Between Groups	.238	1	.238	.236	.628
	Within Groups	123.762	123	1.006		
	Total	124.000	124			
Gains	Between Groups	6.379	1	6.379	6.668	.011
	Within Groups	118.621	124	.957		
	Total	125.000	125			
Losses	Between Groups	.401	1	.401	.399	.529
	Within Groups	124.599	124	1.005		
	Total	125.000	125			
Loss aversion	Between Groups	.436	1	.436	.434	.511
	Within Groups	124.564	124	1.005		
	Total	125.000	125			

Descriptives

		Mean	Std. Error
OC	Others	-.094	.189
	Economics & Business	.020	.101
Gains	Others	-.489	.102
	Economics & Business	.103	.103
Losses	Others	.123	.171
	Economics & Business	-.026	.102
Loss aversion	Others	-.128	.184
	Economics & Business	.027	.101

TABLE A.12 – Raw data from Simulation Game (1/2)

	STRATEGY GAME											
	1P	1V	2P	2V	3P	3V	4P	4V	5P	5V	6P	6V
1	17.0%	100	16.0%	200	17.0%	150	14.0%	300	17.0%	150	16.0%	100
2	16.0%	150	17.0%	125	16.0%	190	14.5%	270	17.0%	0	15.0%	250
3	10.0%	100	15.0%	200	12.5%	250	13.0%	250	12.0%	240	14.0%	280
4	13.0%	200	18.0%	50	16.0%	150	10.0%	200	16.0%	150	14.0%	300
5	15.2%	200	18.0%	0	17.0%	150	16.0%	200	15.0%	250	12.0%	400
6	16.5%	175	15.0%	250	15.0%	250	15.7%	215	17.0%	150	15.5%	225
7	14.5%	250	13.5%	0	14.6%	250	16.5%	175	16.5%	175	15.5%	225
8	17.0%	150	17.0%	150	18.0%	100	17.9%	105	17.0%	150	16.0%	200
9	19.0%	0	18.5%	65	17.0%	130	18.0%	85	17.5%	125	18.0%	100
10	16.0%	200	16.0%	150	16.0%	120	17.0%	120	16.0%	150	13.0%	300
11	15.7%	215	16.8%	160	15.4%	230	18.5%	75	17.5%	100	14.0%	300
12	18.0%	90	19.0%	0	14.0%	280	16.0%	150	15.0%	230	17.0%	120
13	18.0%	100	16.0%	150	14.5%	275	15.2%	240	16.5%	175	14.2%	290
14	17.0%	150	17.0%	150	18.0%	100	15.5%	225	18.5%	75	18.0%	100
15	16.5%	175	18.5%	75	16.5%	175	18.0%	100	19.0%	50	17.5%	125
16	16.0%	0	18.5%	75	15.0%	250	15.0%	250	15.0%	250	13.0%	350
17	16.7%	165	17.1%	145	16.9%	155	14.9%	255	15.3%	235	15.8%	210
18	15.0%	150	15.0%	250	15.0%	250	15.0%	250	15.0%	160	15.0%	250
19	16.0%	200	17.0%	150	15.0%	250	15.0%	250	15.0%	250	15.0%	250
20	16.0%	170	15.0%	210	16.0%	200	16.0%	190	16.5%	175	17.0%	150
21	17.0%	150	17.0%	150	17.0%	150	18.0%	100	16.0%	200	16.0%	200
22	12.0%	400	0.1%	0	12.0%	10	16.0%	200	15.0%	250	15.0%	240
23	16.0%	200	15.0%	250	14.0%	300	15.0%	250	15.0%	250	15.0%	250
24	16.4%	180	18.0%	0	16.0%	200	15.0%	250	16.0%	200	16.0%	200
25	17.0%	100	18.0%	75	14.0%	300	13.5%	300	14.0%	300	14.0%	300
26	16.5%	175	18.0%	100	15.0%	200	17.0%	150	11.0%	0	16.8%	163
27	17.5%	120	15.8%	210	17.2%	135	18.1%	95	20.0%	0	16.9%	155
28	16.5%	170	15.4%	200	14.4%	270	16.5%	165	16.7%	160	14.5%	275
29	17.0%	150	20.0%	0	18.0%	100	18.0%	100	19.0%	50	17.0%	150
30	17.5%	120	17.6%	120	16.0%	170	16.0%	190	17.0%	150	15.5%	225
31	17.1%	145	16.0%	200	16.0%	200	16.5%	150	16.9%	140	16.0%	200
32	17.0%	150	14.0%	225	15.0%	225	15.3%	150	16.4%	150	13.3%	335
33	17.0%	150	0.0%	0	16.5%	175	16.5%	175	16.5%	175	14.9%	255
34	17.0%	150	15.0%	250	14.0%	300	15.0%	250	15.0%	250	16.0%	200
35	16.0%	180	15.0%	0	15.5%	200	15.5%	200	15.0%	250	14.4%	280
36	17.0%	125	20.0%	0	16.0%	180	13.2%	320	13.6%	300	15.5%	220
37	18.0%	100	17.0%	150	13.0%	350	18.0%	100	18.0%	100	16.0%	200
38	19.0%	25	19.0%	50	19.0%	50	19.0%	50	16.5%	175	16.0%	200
39	17.5%	125	20.0%	0	16.0%	200	15.5%	225	15.0%	250	12.0%	400
40	17.0%	150	18.0%	100	15.0%	250	16.0%	200	18.0%	100	16.0%	200
41	15.0%	250	15.0%	250	15.0%	250	16.0%	200	17.0%	150	15.0%	250
42	17.3%	138	17.3%	125	16.0%	200	19.0%	35	20.0%	0	16.0%	200
43	18.0%	90	19.0%	0	16.0%	200	15.0%	250	16.0%	200	15.0%	250
44	17.5%	110	15.0%	225	16.0%	180	17.0%	150	17.0%	130	16.0%	200
45	16.0%	200	15.0%	250	16.0%	200	15.0%	0	18.0%	0	17.0%	150
46	17.3%	130	16.0%	190	14.0%	225	10.5%	465	16.0%	175	13.0%	345
47	15.5%	225	15.1%	245	16.0%	200	16.5%	175	19.0%	50	16.4%	180
48	17.0%	150	19.0%	30	18.0%	100	15.0%	225	13.0%	300	17.0%	150
49	13.0%	200	15.0%	100	18.0%	0	10.0%	250	13.0%	350	17.0%	100
50	17.2%	140	18.6%	70	17.6%	120	16.5%	175	15.0%	250	17.4%	130
51	17.5%	125	16.0%	200	15.5%	225	15.0%	250	16.0%	200	15.0%	250
52	15.0%	100	12.5%	320	12.5%	200	16.0%	0	14.5%	275	13.0%	350
53	14.0%	200	18.0%	50	13.0%	250	12.0%	400	15.0%	250	16.0%	200
54	13.4%	290	17.6%	100	17.3%	130	15.3%	235	15.3%	235	16.0%	200
55	17.0%	130	17.0%	140	14.0%	280	13.0%	310	14.5%	250	14.5%	265
56	17.5%	120	16.8%	160	16.9%	155	15.5%	225	15.4%	230	15.9%	205
57	17.4%	100	16.0%	0	12.0%	400	12.4%	350	12.0%	400	14.6%	270
58	14.0%	200	18.0%	100	17.0%	150	18.0%	100	15.0%	250	16.0%	200
59	17.0%	150	15.0%	250	15.0%	250	14.0%	300	15.0%	250	16.0%	200
60	14.5%	250	14.3%	288	14.8%	250	14.5%	275	14.6%	270	13.5%	250
61	17.0%	150	0.0%	0	15.0%	250	15.0%	250	15.0%	250	15.0%	250
62	16.5%	175	16.5%	175	13.0%	350	15.0%	250	16.0%	200	16.0%	200
63	17.0%	150	18.0%	100	16.0%	200	15.5%	225	16.0%	200	16.3%	185
64	12.0%	30	0.0%	0	15.1%	245	15.8%	210	15.5%	225	15.5%	225
65	16.0%	200	0.0%	0	16.0%	200	16.6%	170	16.0%	200	16.3%	185
66	13.5%	300	14.0%	275	14.0%	300	18.0%	75	20.0%	0	15.0%	225
67	14.6%	255	17.3%	115	15.0%	230	16.0%	0	15.0%	245	15.5%	221
68	15.6%	220	18.0%	100	14.3%	285	15.4%	230	16.2%	190	16.7%	165
69	17.7%	110	14.7%	260	12.5%	370	18.0%	0	16.0%	0	16.0%	200
70	17.3%	138	18.0%	100	16.0%	200	15.0%	250	16.5%	175	14.0%	300

TABLE A.12 – Raw data from Simulation Game (2/2)

	STRATEGY GAME											
	1P	1V	2P	2V	3P	3V	4P	4V	5P	5V	6P	6V
71	17.3%	135	17.4%	130	16.4%	180	16.2%	190	15.7%	215	13.0%	350
72	17.0%	150	16.0%	200	14.0%	300	16.0%	200	16.0%	200	16.0%	200
73	16.0%	200	17.0%	150	18.0%	100	18.0%	100	18.0%	100	15.7%	218
74	16.5%	175	13.0%	300	10.0%	500	16.5%	175	17.0%	150	13.0%	350
75	17.9%	100	16.0%	200	17.0%	150	14.6%	270	18.0%	100	18.7%	65
76	15.0%	200	15.0%	250	16.0%	200	14.0%	250	16.0%	200	14.0%	280
77	17.4%	130	16.1%	195	16.0%	200	18.1%	85	19.2%	30	16.7%	165
78	18.2%	75	17.0%	150	16.8%	160	19.5%	17	19.5%	10	19.5%	25
79	16.0%	200	16.2%	180	15.5%	225	16.5%	100	15.5%	225	16.0%	195
80	16.8%	160	15.0%	250	13.6%	320	18.0%	100	18.0%	100	14.5%	275
81	16.2%	190	10.0%	0	16.0%	200	16.0%	200	17.0%	150	17.0%	150
82	16.5%	150	18.5%	75	16.5%	175	16.5%	175	16.0%	200	17.5%	125
83	18.0%	100	16.0%	200	17.0%	150	14.5%	275	18.0%	100	18.3%	85
84	15.4%	185	16.2%	180	11.9%	400	16.0%	200	14.5%	270	13.9%	305
85	16.7%	165	17.0%	150	15.6%	220	18.0%	100	18.0%	20	14.6%	270
86	17.5%	125	13.0%	350	15.0%	250	18.0%	100	16.0%	200	16.0%	200
87	18.0%	0	17.0%	150	17.0%	150	17.0%	150	17.0%	150	17.0%	150
88	17.5%	110	16.0%	100	12.8%	360	14.0%	300	15.1%	245	14.3%	285
89	16.0%	200	15.0%	200	12.0%	400	13.0%	350	14.5%	275	16.0%	200
90	18.0%	100	12.0%	200	16.0%	200	14.0%	300	13.5%	325	16.0%	200
91	18.0%	100	20.0%	0	18.0%	100	15.6%	220	14.8%	260	15.8%	210
92	11.0%	450	16.0%	200	14.9%	258	13.2%	340	14.3%	285	15.0%	250
93	18.0%	50	15.5%	225	14.5%	275	18.5%	75	17.8%	110	13.9%	305
94	14.5%	275	15.0%	250	16.0%	200	15.0%	220	12.0%	0	17.0%	150
95	16.0%	200	16.0%	200	16.0%	200	16.0%	200	15.6%	220	15.2%	240
96	19.0%	40	17.0%	150	14.0%	300	15.0%	250	16.0%	100	19.0%	30
97	18.0%	20	17.0%	150	16.0%	190	17.5%	100	19.0%	0	16.5%	175
98	14.5%	170	11.3%	400	14.0%	300	18.5%	10	18.0%	45	17.0%	150
99	17.2%	140	17.2%	140	15.0%	250	15.0%	250	16.2%	190	17.5%	125
100	18.0%	75	18.0%	100	16.0%	200	10.0%	500	14.0%	300	16.0%	200
101	13.0%	350	14.5%	275	17.0%	150	18.0%	100	14.5%	275	17.0%	150
102	14.6%	265	18.0%	100	14.8%	255	16.1%	192	15.8%	210	14.7%	265
103	16.3%	170	16.7%	150	16.8%	145	17.3%	127	15.1%	240	13.6%	315
104	16.0%	20	15.5%	25	12.0%	380	10.5%	425	12.0%	350	15.0%	250
105	18.0%	100	18.0%	100	16.0%	200	15.0%	0	13.0%	350	14.0%	300
106	14.5%	6	11.0%	10	14.5%	100	17.0%	60	17.0%	80	13.0%	115
107	18.0%	100	18.0%	100	12.5%	375	18.0%	100	14.0%	300	16.9%	155
108	17.0%	150	17.0%	130	14.5%	275	14.0%	0	19.0%	0	17.0%	150
109	18.2%	90	18.4%	75	14.8%	240	16.0%	200	16.9%	155	14.7%	265
110	17.0%	150	16.0%	200	15.5%	225	15.5%	225	16.5%	175	16.0%	0
111	16.0%	200	16.0%	200	16.0%	200	15.0%	250	15.5%	225	16.0%	200
112	19.0%	0	19.0%	0	14.0%	300	11.0%	450	15.0%	250	15.0%	250
113	16.0%	195	17.5%	120	17.5%	120	18.0%	95	16.5%	175	16.5%	175
114	18.0%	100	0.0%	0	17.0%	150	16.0%	200	16.0%	200	16.0%	200
115	17.0%	150	17.0%	150	17.0%	150	16.0%	200	17.0%	150	17.0%	150
116	16.5%	175	18.1%	95	15.4%	230	17.0%	150	17.0%	0	17.6%	120
117	18.0%	100	16.0%	200	15.0%	250	16.0%	200	16.0%	200	14.5%	275
118	14.0%	200	17.0%	150	15.0%	250	17.5%	125	17.0%	150	14.0%	300
119	14.0%	200	16.0%	150	14.8%	200	15.5%	160	14.0%	250	16.0%	200
120	13.0%	350	15.0%	100	13.0%	325	14.0%	300	16.0%	200	15.0%	250
121	18.0%	100	15.0%	250	15.0%	250	19.0%	50	19.0%	50	16.0%	200
122	16.8%	160	16.1%	195	13.9%	305	13.6%	320	15.6%	220	15.6%	220
123	14.0%	290	15.0%	240	12.0%	400	12.0%	400	16.0%	200	14.0%	300
124	18.0%	100	18.0%	0	17.0%	0	16.0%	200	15.0%	250	15.0%	250
125	16.0%	200	16.0%	200	14.0%	300	15.0%	250	15.0%	250	13.0%	350
126	15.0%	200	15.0%	100	14.0%	300	14.0%	300	16.0%	200	14.0%	300
AVRG	16.3%	154.9	15.6%	139.6	15.3%	219.5	15.7%	193.9	16.0%	178.3	15.5%	216.7
MEDIAN	16.8%	150.0	16.1%	150.0	15.5%	200.0	16.0%	200.0	16.0%	200.0	15.9%	202.5

Note: *In order to preserve participants' anonymity, results in Table A12 have been ranked in terms of gender and age.*

TABLE A.13 – Estimated indicators from the Simulation Game (1/2)

	P_{avg}	P_{vol}	VCC	V_{max}	NPL	Q_{avg}	Q_{vol}
1	16.2%	15.8%	1000	0.870	6.1%	0.980	0.941
2	16.4%	15.5%	985	0.916	5.9%	1.052	0.953
3	12.8%	13.0%	1320	0.607	5.7%	0.843	0.878
4	14.5%	13.8%	1050	0.636	6.0%	0.813	0.848
5	15.9%	14.5%	1200	0.968	5.9%	0.943	1.150
6	15.8%	15.7%	1265	1.000	6.0%	1.081	1.077
7	16.3%	15.4%	1075	0.960	6.2%	0.948	1.043
8	17.2%	17.0%	855	1.000	6.2%	1.018	1.027
9	18.2%	17.7%	505	0.918	5.3%	1.037	1.002
10	15.7%	15.3%	1040	0.800	6.1%	1.089	1.127
11	16.3%	15.7%	1080	0.977	5.9%	1.119	1.105
12	16.7%	15.4%	870	0.870	5.7%	0.961	1.067
13	15.7%	15.3%	1230	0.961	5.6%	1.112	1.102
14	17.3%	17.0%	800	1.000	6.4%	0.962	0.939
15	17.7%	17.3%	700	1.000	6.3%	1.019	1.007
16	16.1%	14.6%	1175	1.000	5.2%	1.075	1.045
17	16.1%	15.9%	1165	1.000	6.1%	0.942	0.939
18	15.0%	15.0%	1310	0.873	5.9%	1.000	1.000
19	15.5%	15.4%	1350	1.000	6.0%	0.979	0.989
20	16.1%	16.0%	1095	0.932	6.2%	1.010	1.017
21	16.8%	16.7%	950	1.000	6.1%	1.020	1.011
22	15.0%	14.1%	1100	0.733	7.1%	0.915	0.929
23	15.0%	14.9%	1500	1.000	6.0%	1.045	1.045
24	16.6%	15.8%	1030	1.000	6.1%	0.912	0.982
25	15.1%	14.3%	1375	0.932	5.6%	0.967	0.984
26	17.2%	16.5%	788	0.940	6.1%	1.075	1.029
27	17.6%	16.9%	715	0.986	6.0%	1.114	1.075
28	15.7%	15.4%	1240	0.954	5.8%	1.122	1.126
29	18.2%	17.5%	550	1.000	6.3%	0.982	1.015
30	16.6%	16.4%	975	0.956	5.9%	1.029	1.035
31	16.4%	16.3%	1035	0.963	6.0%	1.052	1.052
32	15.2%	14.8%	1235	0.852	5.7%	1.151	1.161
33	16.9%	16.1%	930	1.000	5.9%	0.973	1.071
34	15.3%	15.1%	1400	1.000	5.9%	1.044	1.040
35	16.1%	15.2%	1110	0.941	6.0%	0.932	1.039
36	15.9%	14.6%	1145	0.927	6.0%	0.850	0.890
37	16.7%	15.7%	1000	1.000	5.5%	1.174	1.223
38	18.1%	17.1%	550	0.957	5.5%	1.009	1.015
39	16.0%	14.5%	1200	1.000	5.6%	1.000	1.178
40	16.7%	16.3%	1000	1.000	5.9%	1.041	1.055
41	15.5%	15.4%	1350	1.000	6.2%	1.067	1.056
42	17.6%	16.6%	698	0.962	5.7%	1.142	1.080
43	16.7%	15.7%	990	0.990	5.6%	0.961	1.028
44	16.4%	16.2%	995	0.926	5.9%	1.096	1.097
45	17.3%	15.9%	800	1.000	6.2%	1.167	1.011
46	14.5%	13.5%	1530	0.922	5.8%	1.019	0.918
47	16.4%	16.0%	1075	1.000	6.3%	1.074	1.033
48	16.5%	15.4%	955	0.910	6.3%	0.833	0.828
49	14.7%	12.9%	1000	0.625	6.8%	0.692	0.754
50	17.1%	16.6%	885	1.000	6.3%	0.909	0.903
51	15.8%	15.7%	1250	1.000	5.8%	1.043	1.028
52	14.6%	13.3%	1245	0.766	5.6%	1.303	1.152
53	14.7%	13.9%	1350	0.844	6.1%	0.872	0.908
54	15.8%	15.4%	1190	0.948	6.6%	0.864	0.869
55	15.0%	14.6%	1375	0.917	5.8%	0.978	0.966
56	16.3%	16.2%	1095	0.995	6.0%	0.976	0.964
57	14.7%	12.9%	1520	0.961	5.6%	0.896	0.981
58	16.3%	15.9%	1000	0.909	6.3%	0.922	0.905
59	15.3%	15.1%	1400	1.000	6.0%	1.000	0.981
60	14.4%	14.4%	1583	0.934	6.2%	1.026	1.026
61	16.2%	15.3%	1150	1.000	5.8%	0.940	1.031
62	15.5%	15.2%	1350	1.000	5.9%	1.044	1.073
63	16.5%	16.3%	1060	1.000	6.0%	0.964	0.972
64	15.7%	15.4%	935	0.716	5.3%	0.856	1.008
65	16.8%	16.2%	955	1.000	6.2%	0.929	1.002

TABLE A.13 – Estimated indicators from the Simulation Game (2/2)

	P_{avg}	P_{vol}	VCC	V_{max}	NPL	Q_{avg}	Q_{vol}
66	15.8%	14.3%	1175	0.922	6.2%	1.198	1.008
67	16.2%	15.3%	1066	0.941	6.3%	1.039	0.945
68	16.0%	15.7%	1190	1.000	6.2%	0.963	1.001
69	16.8%	14.5%	940	0.984	5.4%	1.336	1.261
70	16.1%	15.7%	1163	1.000	5.8%	1.016	1.045
71	16.0%	15.5%	1200	1.000	5.7%	1.051	1.100
72	15.8%	15.6%	1250	1.000	5.9%	1.065	1.075
73	17.1%	16.8%	868	1.000	6.3%	1.027	1.025
74	14.3%	13.2%	1650	0.971	5.6%	1.389	1.424
75	17.0%	16.4%	885	0.994	6.2%	0.977	0.955
76	15.0%	14.9%	1380	0.920	6.1%	1.000	1.002
77	17.3%	16.7%	805	0.976	5.9%	1.121	1.100
78	18.4%	17.4%	437	0.920	6.0%	1.073	1.085
79	16.0%	15.9%	1125	0.926	6.1%	1.006	1.001
80	16.0%	15.3%	1205	1.000	5.7%	1.225	1.221
81	17.0%	16.4%	890	1.000	6.2%	0.928	0.995
82	16.9%	16.7%	900	0.973	6.2%	0.933	0.946
83	17.0%	16.4%	910	1.000	6.1%	0.984	0.951
84	14.7%	14.2%	1540	0.960	5.8%	1.093	1.130
85	16.7%	16.0%	925	0.920	5.8%	1.117	1.112
86	15.9%	15.3%	1225	1.000	5.9%	1.170	1.176
87	17.5%	17.0%	750	1.000	5.4%	1.059	1.000
88	15.0%	14.4%	1400	0.924	5.6%	1.081	1.087
89	14.4%	14.0%	1625	0.970	6.0%	1.012	1.035
90	14.9%	14.5%	1325	0.869	5.9%	1.034	0.977
91	17.0%	16.0%	890	1.000	6.0%	0.900	0.948
92	14.1%	13.6%	1783	1.000	6.6%	0.840	0.825
93	16.4%	15.3%	1040	0.954	5.3%	1.237	1.241
94	16.3%	15.3%	1095	0.973	6.5%	1.031	0.930
95	15.8%	15.8%	1260	1.000	6.1%	1.008	1.010
96	16.7%	15.4%	870	0.870	5.7%	1.000	1.027
97	17.5%	16.7%	635	0.847	5.2%	1.121	1.068
98	15.5%	13.7%	1075	0.804	6.0%	1.207	1.162
99	16.4%	16.1%	1095	1.000	6.0%	0.974	0.983
100	15.3%	13.6%	1375	0.982	5.9%	0.840	0.735
101	15.7%	14.9%	1300	1.000	6.8%	0.938	0.902
102	15.7%	15.3%	1287	0.990	6.2%	0.979	1.009
103	16.0%	15.5%	1147	0.948	6.0%	1.034	1.058
104	13.5%	12.2%	1450	0.744	5.4%	0.906	0.851
105	16.5%	14.8%	1050	1.000	5.6%	1.063	0.920
106	14.5%	14.9%	371	0.225	5.1%	1.260	1.244
107	16.2%	15.0%	1130	1.000	5.6%	1.055	1.079
108	17.6%	16.0%	705	0.972	5.8%	1.175	1.079
109	16.5%	15.9%	1025	0.976	5.5%	1.067	1.101
110	16.8%	16.0%	975	1.000	6.4%	0.951	1.031
111	15.8%	15.7%	1275	1.000	6.2%	0.969	0.966
112	15.8%	13.3%	1250	1.000	5.4%	0.939	0.860
113	17.0%	16.8%	880	0.978	6.4%	0.981	0.972
114	17.2%	16.4%	850	1.000	5.8%	0.943	0.998
115	16.8%	16.8%	950	1.000	6.2%	0.980	0.976
116	17.4%	16.6%	770	1.000	6.1%	1.047	1.010
117	15.9%	15.6%	1225	1.000	5.7%	1.099	1.087
118	15.8%	15.4%	1175	0.922	5.9%	1.054	1.058
119	15.1%	14.9%	1160	0.781	6.2%	0.929	0.925
120	14.3%	14.0%	1525	0.897	6.3%	1.000	1.002
121	17.0%	16.0%	900	1.000	5.6%	1.217	1.210
122	15.3%	15.0%	1420	1.000	5.9%	1.009	0.996
123	13.8%	13.5%	1830	0.989	6.0%	1.024	1.011
124	17.3%	15.6%	800	1.000	6.1%	0.891	1.061
125	14.8%	14.6%	1550	1.000	5.9%	1.070	1.087
126	14.7%	14.5%	1400	0.875	5.9%	1.047	1.051

Note: *In order to preserve participants' anonymity, results in Table A13 have been ranked in terms of gender and age.*

TABLE A.14 – Histograms of game indicators

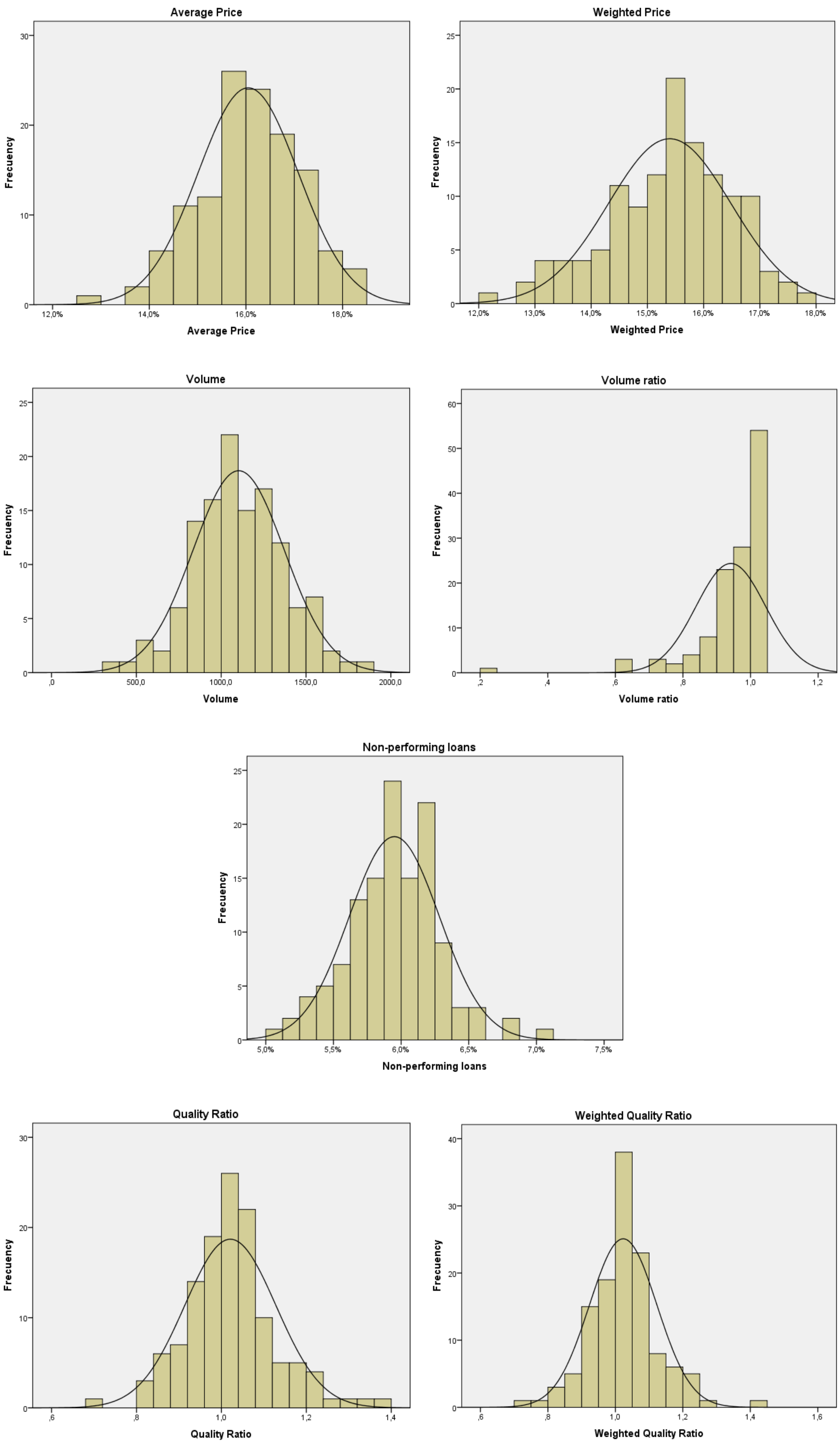
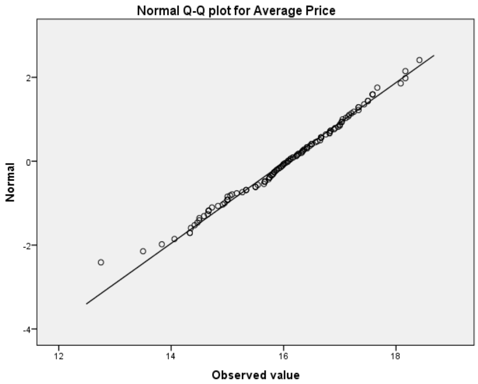
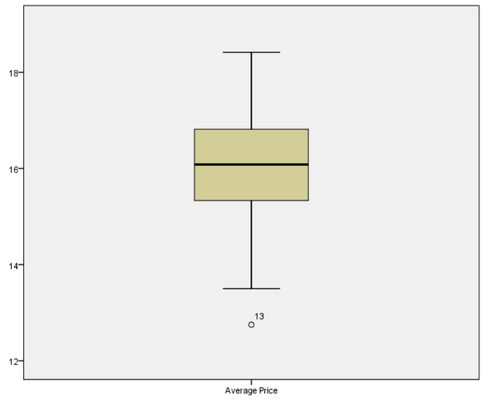
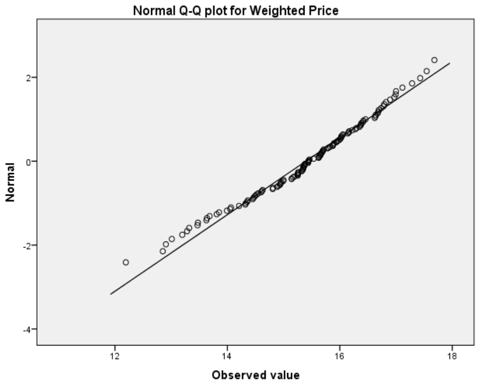
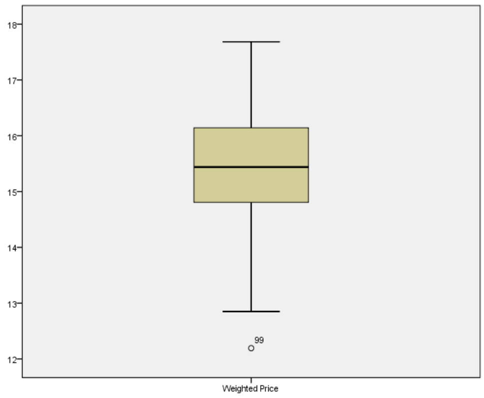


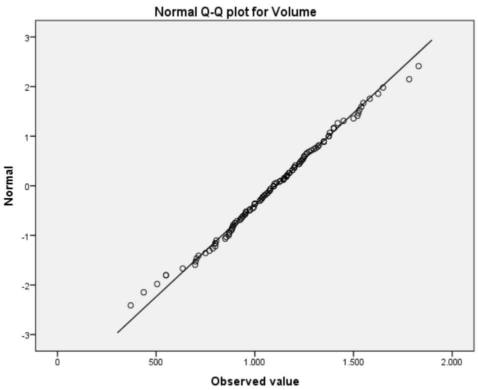
TABLE A.15 – Normal Q-Q plot and Box-and-whiskers plot of game indicators (1/2)

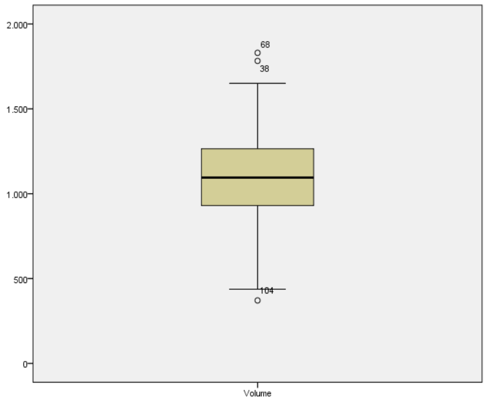


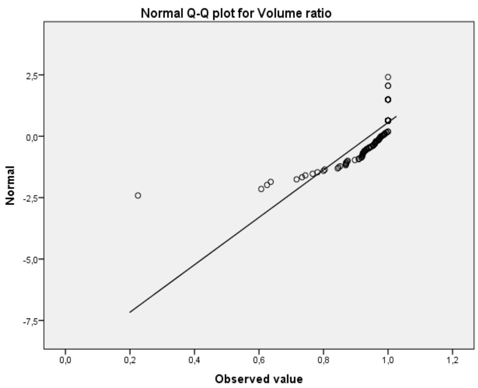












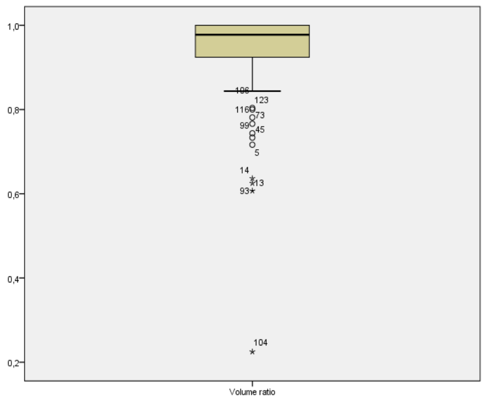
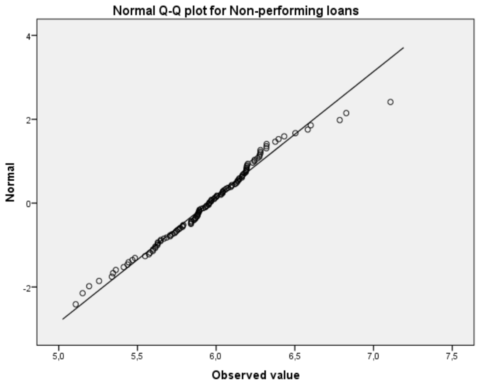
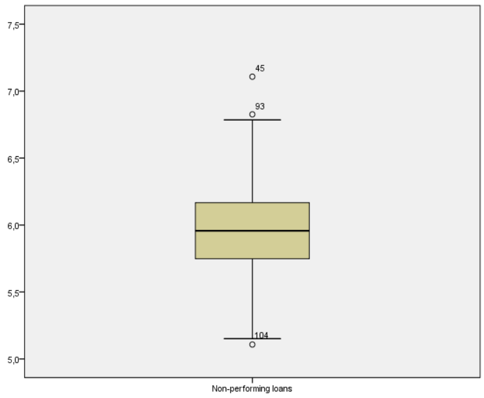
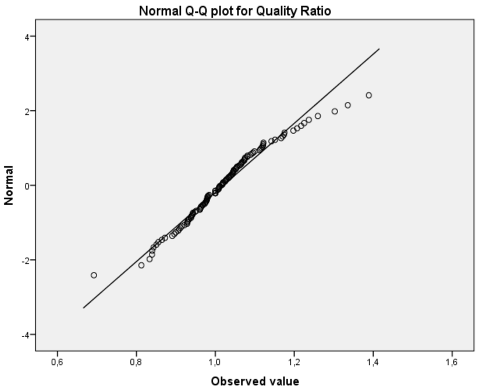
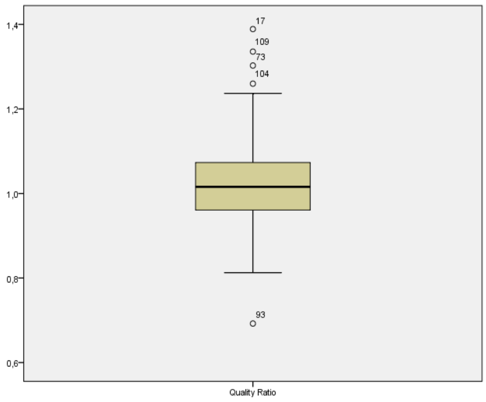


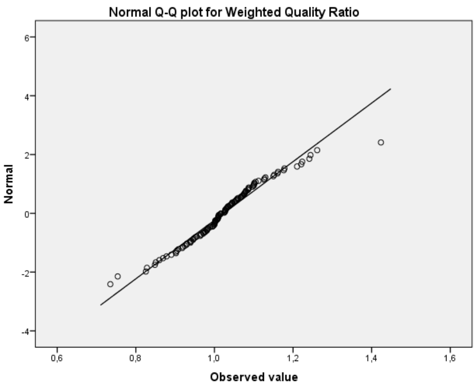
TABLE A.15 – Normal Q-Q plot and Box-and-whiskers plot of game indicators (2/2)











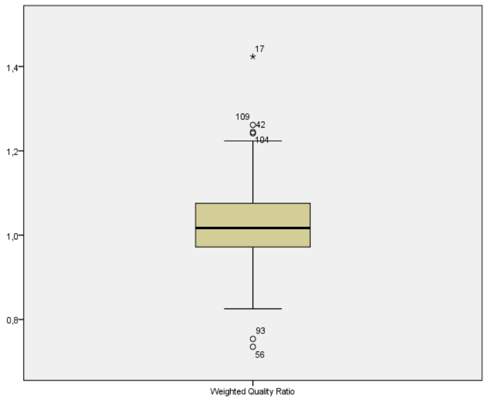


TABLE A.16 – Regression models. Game indicators to behavioral biases (1/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Overprecisión 2		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Average Price

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.184[a]	.034	.026	.010

a. Predictors: (Constant), Overprecisión 2

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.422	1	4.422	4.197	.043[b]
	Residual	126.444	120	1.054		
	Total	130.865	121			

a. Dependent Variable: Average Price
b. Predictors: (Constant), Overprecisión 2

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	15.743	.175		90.120	.000
	Overprecisión 2	.655	.320	.184	2.049	.043

a. Dependent Variable: Average Price

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Overestimation	-.010[b]	-0.107	.915	-.010	.972
	Overplacement	-.107[b]	-1.181	.240	-.108	.979
	Overprecision 1	-.034[b]	-.278	.782	-.025	.548
	alpha +	-.096[b]	-1.065	.289	-.097	.991
	alpha -	.112[b]	1.253	.213	.114	.998
	gamma +	-.118[b]	-1.323	.188	-.120	1.000
	gamma -	.035[b]	.384	.702	.035	.979
	loss aversion 1	-.066[b]	-.723	.471	-.066	.985
	Loss aversion 2 (r)	-.015[b]	-.163	.871	-.015	.963

a. Dependent Variable: Average Price
b. Predictors in the Model: (Constant), Overprecisión 2

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
2	gamma -		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Volume ratio (r)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	.297[a]	.088	.080	.061

a. Predictors: (Constant), gamma -

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	.042	1	.042	11.287	.001[b]
	Residual	0.434	117	.004		
	Total	0.475	118			

a. Dependent Variable: Volume ratio (r)
b. Predictors: (Constant), gamma -

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	.920	.012		76.798	.000
	gamma -	.068	.020	.297	3.360	.001

a. Dependent Variable: Volume ratio (r)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
2	Overestimation	-.102[b]	-1.154	.251	-.107	.999
	Overplacement	-.090[b]	-1.015	.312	-.094	.995
	Overprecision 1	.079[b]	.879	.381	.081	.973
	Overprecisión 2	.079[b]	.880	.381	.081	.979
	alpha +	-.044[b]	-.488	.627	-.045	.982
	alpha -	-.019[b]	-.205	.838	-.019	.894
	gamma +	.101[b]	1.112	.268	.103	.937
	loss aversion 1	-.045[b]	-.505	.614	-.047	.999
	Loss aversion 2 (r)	-.023[b]	-.259	.796	-.024	1.000

a. Dependent Variable: Volume ratio (r)
b. Predictors in the Model: (Constant), gamma -

TABLE A.16 – Regression models. Game indicators to behavioral biases (2/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
3	gamma -		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Non-performing loans

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	.219[a]	.048	.040	.003

a. Predictors: (Constant), gamma -

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
3	Regression	.645	1	.645	6.054	.015[b]
	Residual	12.791	120	.107		
	Total	13.436	121			

a. Dependent Variable: Non-performing loans
b. Predictors: (Constant), gamma -

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
3	(Constant)	5.812	.063		91.620	.000
	gamma -	.263	.107	.219	2.460	.015

a. Dependent Variable: Non-performing loans

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
3	Overestimation	.080[b]	0.899	.371	.082	.999
	Overplacement	-.013[b]	-.145	.885	-.013	.995
	Overprecision 1	-.079[b]	-.869	.387	-.079	.973
	Overprecisión 2	-.040[b]	-.440	.661	-.040	.979
	alpha +	.118[b]	1.316	.191	.120	.982
	alpha -	-.081[b]	-.863	.390	-.079	.894
	gamma +	.146[b]	1.599	.112	.145	.937
	loss aversion 1	-.057[b]	-.643	.522	-.059	.999
	Loss aversion 2 (r)	-.058[b]	-.650	.517	-.059	1.000

a. Dependent Variable: Non-performing loans
b. Predictors in the Model: (Constant), gamma -

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
4	gamma +		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Quality Ratio

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	.258[a]	.066	.059	.104

a. Predictors: (Constant), gamma +

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
4	Regression	.093	1	.093	8.526	.004[b]
	Residual	1.306	120	.011		
	Total	1.398	121			

a. Dependent Variable: Quality Ratio
b. Predictors: (Constant), gamma +

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
4	(Constant)	1.091	.026		42.556	.000
	gamma +	-.108	.037	-.258	-2.920	.004

a. Dependent Variable: Quality Ratio

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
4	Overestimation	.016[b]	0.184	.854	.017	.997
	Overplacement	.124[b]	1.405	.163	.128	.989
	Overprecision 1	.126[b]	1.429	.156	.130	.999
	Overprecisión 2	.049[b]	.555	.580	.051	1.000
	alpha +	-.137[b]	-1.252	.213	-.114	.643
	alpha -	.050[b]	.559	.577	.051	.991
	gamma -	.124[b]	1.365	.175	.124	.937
	loss aversion 1	-.089[b]	-1.010	.314	-.092	.995
	Loss aversion 2 (r)	-.037[b]	-.416	.678	-.038	.991

a. Dependent Variable: Quality Ratio
b. Predictors in the Model: (Constant), gamma +

TABLE A.16 – Regression models. Game indicators to behavioral biases (3/3)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
5	gamma +		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).
6	Overprecision 1		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Weighted Quality (r)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
5	.216[a]	.047	.039	.09199
6	.298[b]	.089	.073	.09031

a. Predictors: (Constant), gamma +

b. Predictors: (Constant), gamma +, Overprecision 1

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
5	Regression	.050	1	.050	5.886	.017[b]
	Residual	1.015	120	.008		
	Total	1.065	121			
6	Regression	.095	2	.047	5.797	.004[c]
	Residual	.971	119	.008		
	Total	1.065	121			

a. Dependent Variable: Weighted Quality (r)

b. Predictors: (Constant), gamma +

c. Predictors: (Constant), gamma +, Overprecision 1

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
5	(Constant)	1.071	.023		47.387	.000
	gamma +	-.079	.033	-.216	-2.426	.017
6	(Constant)	1.047	.024		42.795	.000
	gamma +	-.082	.032	-.223	-2.545	.012
	Overprecision 1	.075	.032	.205	2.343	.021

a. Dependent Variable: Weighted Quality (r)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
5	Overestimation	-.009[b]	-.100	.920	-.009	.997
	Overplacement	.095[b]	1.059	.292	.097	.989
	Overprecision 1	.205[b]	2.343	.021	.210	.999
	Overprecisión 2	.039[b]	.431	.667	.039	1.000
	alpha +	-.061[b]	-.549	.584	-.050	.643
	alpha -	-.016[b]	-.178	.859	-.016	.991
	gamma -	-.006[b]	-.063	.950	-.006	.937
	loss aversion 1	-.100[b]	-1.117	.266	-.102	.995
	Loss aversion 2 (r)	-.016[b]	-.177	.860	-.016	.991
6	Overestimation	.017[c]	.190	.850	.017	.981
	Overplacement	.104[c]	1.182	.240	.108	.987
	Overprecisión 2	-.182[c]	-1.546	.125	-.141	.546
	alpha +	-.017[c]	-.154	.878	-.014	.623
	alpha -	-.018[c]	-.206	.837	-.019	.991
	gamma -	-.041[c]	-.450	.654	-.041	.913
	loss aversion 1	-.111[c]	-1.269	.207	-.116	.992
	Loss aversion 2 (r)	-.035[c]	-.395	.694	-.036	.982

a. Dependent Variable: Weighted Quality (r)

b. Predictors in the Model: (Constant), gamma +

c. Predictors in the Model: (Constant), gamma +, Overprecision 1

TABLE A.17 – Factorial analysis. Correlations

VARIABLES TO FACTORS

Correlations

		E	P	Mmed	Mavg	alpha +	alpha -	gamma +	gamma -	βmed	βavg (r)
Strategy	Pearson Correlation	-.049	-.121	.061	.145	-.059	.135	-.095	.029	-.032	.024
	Sig. (2-tailed)	.590	.180	.499	.108	.515	.133	.293	.745	.720	.795
	N	125	125	124	124	125	125	125	125	125	122
Quality	Pearson Correlation	-.037	.051	.150	.040	-,196*	.017	-,269**	-.091	-.056	.009
	Sig. (2-tailed)	.678	.571	.097	.660	.028	.853	.002	.314	.538	.917
	N	125	125	124	124	125	125	125	125	125	122

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

FACTORS TO INDICATORS

Correlations

		Pavg	Pvol	VCCind	VMAXind (r)	NPL	Qavg	Qvol (r)
OC	Pearson Correlation	-.103	-.122	.111	-.112	.046	.038	.001
	Sig. (2-tailed)	.252	.175	.220	.223	.613	.671	.994
	N	125	125	125	121	125	125	124
Gains	Pearson Correlation	-.139	-.079	.085	.051	.157	-,285**	-,223*
	Sig. (2-tailed)	.120	.381	.346	.577	.078	.001	.013
	N	126	126	126	122	126	126	125
Losses	Pearson Correlation	.093	.116	.069	,299**	,189*	.068	-.042
	Sig. (2-tailed)	.301	.197	.444	.001	.035	.450	.644
	N	126	126	126	122	126	126	125
Loss aversion	Pearson Correlation	-.008	.000	-.032	-.076	-.085	-.061	-.072
	Sig. (2-tailed)	.933	.999	.721	.406	.345	.501	.426
	N	126	126	126	122	126	126	125

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

TABLE A.18 – Factorial analysis. Regressions (1/5)

FACTORS TO FACTORS

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Gains		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Quality

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.266[a]	.071	.063	.948

a. Predictors: (Constant), Gains

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.363	1	8.363	9.297	.003[b]
	Residual	109.740	122	.900		
	Total	118.103	123			

a. Dependent Variable: Quality

b. Predictors: (Constant), Gains

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.016	.085		-.183	.855
	Gains	-.261	.086	-.266	-3.049	.003

a. Dependent Variable: Quality

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Overconfidence	-.016[b]	-.187	.852	-.017	1.000
	Losses	-.069[b]	-.789	.432	-.072	1.000
	Loss aversion Factor	-.040[b]	-.458	.648	-.042	1.000

a. Dependent Variable: Quality

b. Predictors in the Model: (Constant), Gains

TABLE A.18 – Factorial analysis. Regressions (2/5)

VARIABLES TO FACTORS

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	gamma +		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Quality

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.269[a]	.072	.064	.948

a. Predictors: (Constant), gamma +

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.377	1	8.377	9.324	.003[b]
	Residual	107.806	120	.898		
	Total	116.183	121			

a. Dependent Variable: Quality

b. Predictors: (Constant), gamma +

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.645	.233		2.772	.006
	gamma +	-1.029	.337	-.269	-3.054	.003

a. Dependent Variable: Quality

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Overestimation	-.023[b]	-.256	.798	-.023	.997
	Overplacement	.080[b]	.903	.368	.083	.989
	Overprecision 1	.158[b]	1.817	.072	.164	.999
	Overprecisión 2	.034[b]	.386	.700	.035	1.000
	alpha +	-.055[b]	-.503	.616	-.046	.643
	alpha -	-.008[b]	-.093	.926	-.009	.991
	gamma -	-.025[b]	-.276	.783	-.025	.937
	loss aversion 1	-.074[b]	-.840	.402	-.077	.995
	Loss aversion 2 (r)	-.017[b]	-.187	.852	-.017	.991

a. Dependent Variable: Quality

b. Predictors in the Model: (Constant), gamma +

TABLE A.18 – Factorial analysis. Regressions (3/5)

	Model 1	Model 2	Model 3	Model 4
Dependent variable	$VMAX_{ind}$	NPL	Q_{avg}	Q_{vol}
Constant	0.955	5.950	1.021	1.020
OC	-	-	-	-
(signific.)				
Gains	-	-	-0.031	-0.021
(signific.)			0.001	0.013
Losses	0.019	0.063	-	-
(signific.)	0.001	0.035		
Loss Aversio	-	-	-	-
(signific.)				
R^2	0.089	0.036	0.081	0.050
adj. R^2	0.082	0.028	0.074	0.042

TABLE A.18 – Factorial analysis. Regressions (4/5)

FACTORS TO INDICATORS

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Losses		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Volume ratio (r)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.299[a]	.089	.082	.061

a. Predictors: (Constant), Losses

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.043	1	.043	11.684	.001[b]
	Residual	.440	119	.004		
	Total	.483	120			

a. Dependent Variable: Volume ratio (r)

b. Predictors: (Constant), Losses

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.955	.006		172.785	.000
	Losses	.019	.006	.299	3.418	.001

a. Dependent Variable: Volume ratio (r)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	Overconfidence	-.141[b]	-1.615	.109	-.147	.991
	Gains	.051[b]	.581	.562	.053	1.000
	Loss aversion Factor	-.076[b]	-.867	.387	-.080	1.000

a. Dependent Variable: Volume ratio (r)

b. Predictors in the Model: (Constant), Losses

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
2	Losses		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Non-performing loans

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	.189[a]	.036	.028	.003

a. Predictors: (Constant), Losses

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
2	Regression	.489	1	.489	4.532	.035[b]
	Residual	13.280	123	.108		
	Total	13.769	124			

a. Dependent Variable: Non-performing loans

b. Predictors: (Constant), Losses

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
2	(Constant)	5.950	.029		202.449	.000
	Losses	.063	.030	.189	2.129	.035

a. Dependent Variable: Non-performing loans

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
2	Overconfidence	.028[b]	.316	.752	.029	.991
	Gains	.157[b]	1.794	.075	.160	1.000
	Loss aversion Factor	-.085[b]	-.957	.341	-.086	1.000

a. Dependent Variable: Non-performing loans

b. Predictors in the Model: (Constant), Losses

TABLE A.18 – Factorial analysis. Regressions (5/5)

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
3	Gains		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Quality Ratio

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	.285[a]	.081	.074	.103

a. Predictors: (Constant), Gains

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
3	Regression	.116	1	.116	10.866	.001[b]
	Residual	1.317	123	.011		
	Total	1.433	124			

a. Dependent Variable: Quality Ratio
b. Predictors: (Constant), Gains

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
3	(Constant)	1.021	.009		110.322	.000
	Gains	-.031	.009	-.285	-3.296	.001

a. Dependent Variable: Quality Ratio

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
3	Overconfidence	.033[b]	.386	.700	.035	1.000
	Losses	.068[b]	.784	.434	.071	1.000
	Loss aversion Factor	-.061[b]	-.699	.486	-.063	1.000

a. Dependent Variable: Quality Ratio
b. Predictors in the Model: (Constant), Gains

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
4	Gains		Stepwise (Criteria: Probab.-of-F-to-enter <= .050, Probab.-of-F-to-remove >= .100).

a. Dependent Variable: Weighted Quality (r)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	.223[a]	.050	.042	.092

a. Predictors: (Constant), Gains

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
4	Regression	.054	1	.054	6.357	.013[b]
	Residual	1.029	122	.008		
	Total	1.083	123			

a. Dependent Variable: Weighted Quality (r)
b. Predictors: (Constant), Gains

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
4	(Constant)	1.020	.008		123.653	.000
	Gains	-.021	.008	-.223	-2.521	.013

a. Dependent Variable: Weighted Quality (r)

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
4	Overconfidence	-.003[b]	-.036	.972	-.003	1.000
	Losses	-.042[b]	-.471	.638	-.043	1.000
	Loss aversion Factor	-.072[b]	-.813	.418	-.074	1.000

a. Dependent Variable: Weighted Quality (r)
b. Predictors in the Model: (Constant), Gains

APPENDIX THEORETICAL MODEL

In this Appendix we provide the formal proof of the results obtained in the model in Chapter 9.

Maxima – Computer Algebra System was used for mathematical derivations.

Proof of Lemma 1. We first calculate the volumes of loans granted in the possible market configurations and the corresponding rates that clear the market.

I. Rational duopoly. If both banks have the unbiased probability θ_l, they simultaneously solve the same problem, which is defined by

$$\begin{aligned}&\max E\Pi^i(L_h^i, L_l^i) = \theta_h \cdot r_h(L_h^i + L_h^{j*})L_h^i - (1-\theta_h)L_h^i + \theta_l \cdot r_l(L_l^i + L_l^{j*})L_l^i - (1-\theta_l)L_l^i - rD^i - C(D, L)\\ &\text{s.t}: L_l^i + L_l^i = D^i\end{aligned} \tag{A1}$$

where *i,j=A,B;i≠j*. Inserting the restriction into the objective function $E\Pi^i(L_h^i, L_l^i)$, (A1) can be rewritten as

$$\max E\Pi^i(L_h^i, L_l^i) = [\theta_h \cdot r_h(L_h^i + L_h^{j*}) - (1-\theta_h) - r]L_h^i + [\theta_l \cdot r_l(L_l^i + L_l^{j*}) - (1-\theta_l) - r]L_l^i - c \cdot (L_h^i + L_l^i) \tag{A2}$$

and the solution of (A2) is given by the pair of volumes of loans

$$L_h^{A*} = L_h^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3\theta_h} \tag{A3}$$

and

$$L_{l,rD}^{A*} = L_{l,rD}^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3\theta_l}, \tag{A4}$$

where L_h^{i*} denotes the volume of loans granted by bank *i* to high-quality borrowers and $L_{l,rD}^{i*}$ stands for the volume of loans granted by bank *i* to low-quality borrowers in a rational duopoly. The subsequent interest rates to be paid are

$$r_h^* = \frac{\alpha}{3\beta} + \frac{2(1+r+c-\theta_h)}{3\theta_h} \tag{A5}$$

and

$$r_{l,rD}^* = \frac{\alpha}{3\beta} + \frac{2(1+r+c-\theta_l)}{3\theta_l}, \tag{A6}$$

where $r_{l,rD}^*$ denotes the equilibrium interest rate for low-quality borrowers in a rational duopoly.

II. Asymmetric market. When a rational bank (bank *A*) and a boundedly rational bank (bank *B*) compete in the industry, they solve two alternative versions of the program given in (A2); namely,

$$\max E\Pi^A(L_h^A, L_l^A) = [\theta_h \cdot r_h(L_h^A + L_h^{B*}) - (1-\theta_h) - r]L_h^A + [\theta_l \cdot r_l(L_l^A + L_l^{B*}) - (1-\theta_l) - r]L_l^A - c\cdot(L_h^A + L_l^A), \tag{A7}$$

the bank A, and

$$\max E\Pi^B(L_h^B, L_l^B) = [\theta_h \cdot r_h(L_h^{A*} + L_h^B) - (1-\theta_h) - r]L_h^B + [\theta_l^O \cdot r_l(L_l^{A*} + L_l^B) - (1-\theta_l^O) - r]L_l^B - c\cdot(L_h^B + L_l^B), \tag{A8}$$

the bank B. The assumption of linear costs ensures that markets are separable, so the volume of loans and the interest rate in the high-quality market are identical to those in the rational and biased duopolies —see (A3) and (A5). However, in the low-quality market, we have the volume of loans

$$L_{l,aD}^{A*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3}\left(\frac{2}{\theta_l} - \frac{1}{\theta_l^O}\right) \tag{A9}$$

and

$$L_{l,aD}^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3}\left(\frac{2}{\theta_l^O} - \frac{1}{\theta_l}\right), \tag{A10}$$

granted by banks A and B, respectively. Finally, the corresponding interest rate that clears the market for low-quality borrowers in this asymmetric duopoly amounts to

$$r_{l,aD}^{*} = \frac{\alpha-2\beta}{3\beta} + \frac{1+r+c}{3}\left(\frac{1}{\theta_l} + \frac{1}{\theta_l^O}\right). \tag{A11}$$

Whenever the no-monopoly condition does not hold, the volume of loans granted by bank A to low-quality borrowers would be $L_{l,aD}^{A*} \leq 0$ according to (A9). Thus, the market for low-quality borrowers would become a monopoly formed by bank B, which would alternatively solve

$$\max E\Pi^B(L_h^B, L_l^B) = [\theta_h \cdot r_h(L_h^B + L_h^{A*}) - (1-\theta_h) - r]L_h^B + [\theta_l^O \cdot r_l(L_l^B) - (1-\theta_l^O) - r]L_l^B - c\cdot(L_h^B + L_l^B), \tag{A12}$$

since high and low-quality markets are separable. The solution of (A12) renders the volume of loans

$$L_{l,M}^{*} = \frac{\alpha+\beta}{2} - \frac{\beta(1+r+c)}{2\theta_l^O}, \tag{A13}$$

where $L_{l,M}^{*}$ denotes the volume of loans granted to low-quality borrowers by bank B as a monopolist. Finally, the interest rate to be paid by low-quality borrowers in a monopoly amounts to

$$r_{l,M}^{*} = \frac{\alpha}{2\beta} + \frac{1+r+c-\theta_l^O}{2\theta_l^O}. \tag{A14}$$

III. <u>Biased duopoly</u>. If both banks are biased in the low-quality market, they solve a similar optimization problem as in (A1), but where the probability of success of low-quality borrowers is now replaced by θ_l^O. Consequently, we get the same strategy for high-quality borrowers (see A3 and A5), whereas for low-quality borrowers we obtain

$$L_{l,bD}^{A*} = L_{l,bD}^{B*} = \frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{3\theta_l^O} \tag{A15}$$

as the volume of loans provided by bank i in a biased duopoly, and

$$r^*_{l,bD} = \frac{\alpha}{3\beta} + \frac{2(1+r+c-\theta_l^O)}{3\theta_l^O} \tag{A16}$$

as the interest rate to be paid by such borrowers. From here, Lemma 1 straightforwardly follows by taking into account (A4), (A9), (A10), (A13) and (A15). First, using (A4) and (A15) we conclude that $L^*_{l,bD} > L^*_{l,rD}$, since $\theta_l^O > \theta_l$. Next, to see what happens in an asymmetric duopoly where one bank is rational and the other biased, consider first the situation where the no-monopoly condition $\theta_l > \theta_l^{\mathrm{M}}$ holds, that is, the situation where we have an asymmetric duopoly. Using (A15) and rearranging, the volume of loans granted in a biased duopoly amounts to

$$L^*_{l,bD} = L^{A*}_{l,bD} + L^{B*}_{l,bD} = \frac{2(\alpha+\beta)}{3} - \frac{2\beta(1+r+c)}{3\theta_l^O}\ , \tag{A17}$$

while (A9) and (A10) render the volume of loans

$$L^*_{l,aD} = L^{A*}_{l,aD} + L^{B*}_{l,aD} = \frac{2(\alpha+\beta)}{3} - \beta(1+r+c)\left(\frac{1}{3\theta_l} + \frac{1}{3\theta_l^O}\right), \tag{A18}$$

which are the volume granted in an asymmetric duopoly. The fact that $\frac{2}{3\theta_l^O} < \frac{1}{3\theta_l} + \frac{1}{3\theta_l^O}$ leads to $L^*_{l,bD} > L^*_{l,aD}$. Besides, using (A4) we get in a rational duopoly the volume of loans

$$L^*_{l,rD} = L^{A*}_{l,rD} + L^{B*}_{l,rD} = \frac{2(\alpha+\beta)}{3} - \frac{2\beta(1+r+c)}{3\theta_l}, \tag{A19}$$

which leads to $L^*_{l,aD} > L^*_{l,rD}$ because $\frac{2}{3\theta_l} < \frac{1}{3\theta_l} + \frac{1}{3\theta_l^O}$.

Finally, when the no-monopoly condition does not hold, i.e. when $\theta_l \le \frac{2\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + \beta(1+r+c)}$, we need to compare the volume of loans granted to low-quality borrowers in the monopoly market, $L^*_{l,M}$, with volumes $L^*_{l,rD}$ and $L^*_{l,bD}$. On one hand, substituting the monopoly condition in $L^*_{l,rD}$, we obtain

$$L^*_{l,rD} = \frac{\alpha+\beta}{6} - \frac{\beta(1+r+c)}{6\theta_l^O}, \tag{A20}$$

which is lower than $L^*_{l,M}$ in (A13). On the other hand, it follows that

$$L^*_{l,bD} = \frac{2}{3}\left[\frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{\theta_l^O}\right] \ge \frac{1}{2}\left[\frac{\alpha+\beta}{3} - \frac{\beta(1+r+c)}{\theta_l^O}\right] = L^*_{l,M} \tag{A21}$$

in any case. This completes the proof of the lemma. ■

Proof of Lemma 2. We need to compare the expected profits that banks would obtain in different market configurations. Consequently, we must be aware that the rational bank A would estimate

$$E\,\Pi^A_x = [\theta_h(1+r^*_h) - (1+r+c)]L^{A*}_h + [\theta_l(1+r^*_{l,x}) - (1+r+c)]L^{A*}_{l,x}\ , \tag{A22}$$

where $L_{l,x}^{A*}$ and $r_{l,x}^{*}$ are, respectively, the volume of loans granted by bank *A* in the market configuration *x*, $x \in \{rD, aD, bD, M\}$, we are considering and the clearing interest rate. The objective function of bank *B* is

$$E\Pi_x^B = [\theta_h(1+r_h^*) - (1+r+c)]L_h^{B*} + [\theta_l^O(1+r_{l,x}^*) - (1+r+c)]L_{l,x}^{B*}, \tag{A23}$$

where θ_l^O replaces θ_l.

In order to prove that playing biased is a dominant strategy for bank *B* we have to check: (i) that the bank *B*'s expected profit in the asymmetric duopoly, $E\Pi_{aD}^B$ (alternatively, in the monopoly $E\Pi_M^B$ when the no-monopoly condition does not hold) is higher than in the rational duopoly, $E\Pi_{rD}^B$, and (ii) that its expected profit in the biased duopoly, $E\Pi_{bD}^B$ is higher than in the inverted duopoly, $E\Pi_{iD}^B$ (alternatively, in the inverted monopoly $E\Pi_{iM}^B$), where in both inverted scenarios the banks' strategies go against their own priors, such that (A9) applies to bank *B*, and (A10) and (A13) apply to bank *A*.

Consider first the case in which the no-monopoly condition holds.

(i) When comparing $E\Pi_{aD}^A = [\theta_h(1+r_h^*) - (1+r+c)]L_h^{A*} + [\theta_l^O(1+r_{l,aD}^*) - (1+r+c)]L_{l,aD}^{A*}$ and $E\Pi_{rD}^B = [\theta_h(1+r_h^*) - (1+r+c)]L_h^{B*} + [\theta_l^O(1+r_{l,rD}^*) - (1+r+c)]L_{l,rD}^{B*}$, the fact that markets are separable implies that $[\theta_l^O(1+r_{l,aD}^*) - (1+r+c)]L_{l,aD}^{B*} > [\theta_l^O(1+r_{l,rD}^*) - (1+r+c)]L_{l,rD}^{B*}$ must be proven. Substituting (A10), (A11), (A4) and (A6) it follows that bank *B* plays biased if and only if

$$\frac{\beta(1+r+c)^2[3(\theta_l^O)^2 - 7\theta_l^O\theta_l + 4(\theta_l)^2] + (\alpha+\beta)(1+r+c)[\theta_l(\theta_l^O)^2 - (\theta_l)^2\theta_l^O]}{9(\theta_l)^2\theta_l^O} > 0 \tag{A24}$$

and (A24) is satisfied for $\alpha > \beta\left[\frac{4(1+r+c)}{\theta_l^O} - \frac{3(1+r+c)}{\theta_l} - 1\right]$, which is true because of Assumption 2.[273]

(ii) Now we compare the expected profits in the biased duopoly $E\Pi_{bD}^B = [\theta_h(1+r_h^*) - (1+r+c)]L_h^{B*} + [\theta_l^O(1+r_{l,bD}^*) - (1+r+c)]L_{l,bD}^{B*}$ with those in the inverted asymmetric duopoly $E\Pi_{iD}^B = [\theta_h(1+r_h^*) - (1+r+c)]L_h^{B*} + [\theta_l^O(1+r_{l,iD}^*) - (1+r+c)]L_{l,iD}^{B*}$. Since markets are separable this requires to prove that $[\theta_l^O(1+r_{l,bD}^*) - (1+r+c)]L_{l,bD}^{B*} > [\theta_l^O(1+r_{l,iD}^*) - (1+r+c)]L_{l,iD}^{B*}$. Substituting (A15), (A16), (A9) —we pick (A9) since $L_{l,iD}^{B*} = L_{l,aD}^{A*}$— and (A11), it follows that bank *B* plays biased if and only if

---

[273] The value of the parameter *α* that makes (A24) equal to zero is $\alpha = \beta\left(\frac{4(1+r+c)}{\theta_l^O} - \frac{3(1+r+c)}{\theta_l} - 1\right)$. Besides, the first derivative of (A24) with respect to *α* is $\frac{1+r+c}{9}\left(\frac{\theta_l^O}{\theta_l} - 1\right)$, which is always positive. Hence, the difference in profits is always positive for any value of parameter *α* above that threshold. Finally, the minimum admissible value of *α* imposed by Assumption 2, $\beta\left(\frac{1+r+c}{\theta_l^O} - 1\right)$, exceeds $\beta\left(\frac{4(1+r+c)}{\theta_l^O} - \frac{3(1+r+c)}{\theta_l} - 1\right)$ since $\theta_l^O > \theta_l$.

$$\frac{\beta(1+r+c)^2[2(\theta_l^O)^2-5\theta_l^O\theta_l+3(\theta_l)^2]+(\alpha+\beta)(1+r+c)[\theta_l(\theta_l^O)^2-(\theta_l)^2\theta_l^O]}{9(\theta_l)^2\theta_l^O}>0 \qquad \text{(A25)}$$

and (A25) is satisfied if $\alpha>\beta\left[\frac{3(1+r+c)}{\theta_l^O}-\frac{2(1+r+c)}{\theta_l}-1\right]$ holds, which is true by virtue of Assumption 2.[274]

Consider now the no-monopoly condition does not hold.

(iii) Following the same logic as above, to prove that $E\Pi_M^B>E\Pi_{rD}^B$, and given that markets are separable, we need to prove that $[\theta_l^O(1+r_{l,M}^*)-(1+r+c)]L_{l,M}^{B*}>[\theta_l^O(1+r_{l,rD}^*)-(1+r+c)]L_{l,rD}^{B*}$. Substituting (A10), (A11), (A4) and (A6), it follows that bank *B* plays biased if and only if

$$\frac{\Psi}{36\beta(\theta_l)^2\theta_l^O}>0, \qquad \text{(A26)}$$

where $\Psi=[8\beta^2(1+r+c)^2-4\beta(\alpha+\beta)(1+r+c)\theta_l+5(\alpha+\beta)^2(\theta_l)^2](\theta_l^O)^2$

$$-[12\beta^2(1+r+c)^2\theta_l+6\beta(\alpha+\beta)(1+r+c)(\theta_l)^2]\theta_l^O+9\beta^2(1+r+c)^2(\theta_l)^2.$$

To prove that $\Psi>0$ only for small values of θ_l as $\theta_l\le\theta_l^{\mathrm{M}}$, we proceed as follows. First, we show that (A26) is positive at $\theta_l=\theta_l^{\mathrm{M}}$.[275] Next, a sufficient condition to have positive profits for values of θ_l below θ_l^{M} is that the first derivative of (A26) with respect to θ_l,

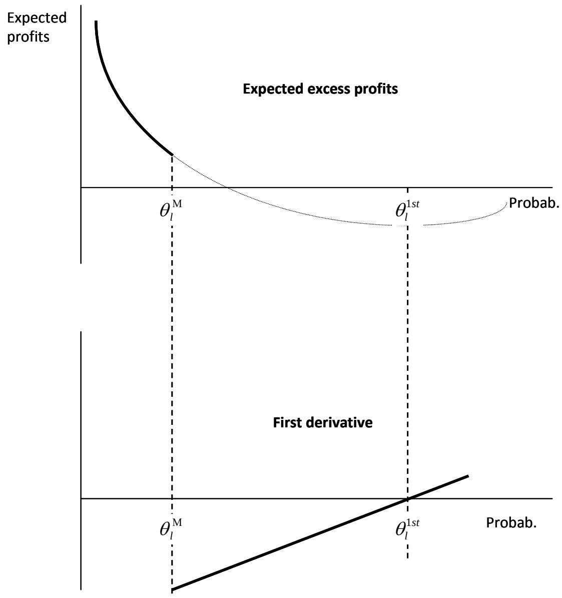
$$\frac{\beta(1+r+c)^2(3\theta_l-4\theta_l^O)+(\alpha+\beta)(1+r+c)\theta_l\theta_l^O}{9(\theta_l)^3}, \qquad \text{(A27)}$$

is negative for all $\theta_l\le\theta_l^{\mathrm{M}}$. The first derivative stated in (A27) is equal to zero at $\theta^{1\mathrm{st}}=\frac{4\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O+3\beta(1+r+c)}$ and negative below that point, since the denominator of (A27) is positive whereas the numerator is negative for all $\theta_l<\theta_l^{1\mathrm{st}}$. It is then easy to prove that $\theta_l^{\mathrm{M}}=\frac{2\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O+\beta(1+r+c)}$ satisfies $\theta_l^{\mathrm{M}}<\theta_l^{1\mathrm{st}}$. We may do this by simply reducing the cross multiplication

[274] This holds for identical reason as in the previous footnote. we solve (A25) = 0 in terms of alpha to find out the alpha that makes profits equal to zero to find it would be $\alpha=3\beta\frac{1+r+c}{\theta_l^O}-2\beta\frac{1+r+c}{\theta_l}-\beta$. The derivative of (A25) with respect to α is the same as in the previous footnote, hence positive. Thus, equation (A25) is increasing, hence positive for all $\alpha>3\beta\frac{1+r+c}{\theta_l^O}-2\beta\frac{1+r+c}{\theta_l}-\beta$. Finally, it is easy to check Assumption 2 imposes a minimum alpha that is higher, since $\beta\frac{1+r+c}{\theta_l^O}-\beta>3\beta\frac{1+r+c}{\theta_l^O}-2\beta\frac{1+r+c}{\theta_l}-\beta$ as long as $\theta_l^O>\theta_l$.

[275] If we substitute θ_l^{M} in (A26) we get $\frac{5[(\alpha+\beta)\theta_l^O-\beta(1+r+c)]^2}{36\beta\theta_l^O}$, which is positive for all values of parameter α except at $\alpha=\frac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$, where it equals zero. However, Assumption 2 imposes $\alpha>\frac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$.

$\left[2\beta(1+r+c)\theta_l^O\right]\times\left[(\alpha+\beta)\theta_l^O+3\beta(1+r+c)\right]<\left[4\beta(1+r+c)\theta_l^O\right]\times\left[(\alpha+\beta)\theta_l^O+\beta(1+r+c)\right]$ to $2\beta^2(1+r+c)^2\theta_l^O-2(\alpha+\beta)(1+r+c)\left(\theta_l^O\right)^2<0$, a condition that simplifies to $\beta(1+r+c)<(\alpha+\beta)\theta_l^O$ which rearranged is simply $\alpha>\beta\dfrac{1+r+c-\theta_l^O}{\theta_l^O}$, ensured by Assumption 2. Consequently, (A27) is negative for values below θ_l^{1st} and hence the profits given in (A26) are positive below θ_l^{M}.



(iv) Finally, in order to prove that $E\Pi_{bD}^B>E\Pi_{iM}^B$, since markets are separable this only requires to check that $[\theta_l^O(1+r_{l,bD}^*)-(1+r+c)]L_{l,bD}^{B*}>0$. Substituting (A15) and (A16) we conclude that bank *B* plays biased if and only if

$$\frac{[(\alpha+\beta)\theta_l^O-\beta(1+r+c)]^2}{9\beta\theta_l^O}>0, \tag{A28}$$

and (A28) holds in all cases except at $\alpha=\dfrac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$, where it equals to zero. However, Assumption 2 that imposes the restriction $\alpha>\dfrac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$ ensures that (A28) always holds. This completes the proof of the lemma. ■

Proof of Lemma 3. Given that playing biased is a dominant strategy for bank *B*, in order to determine the conditions for bank *A* to herd we have to compare its expected profits if bank *A* plays biased (the biased duopoly) and its expected profits if it plays rational and we have the asymmetric duopoly, or the monopoly by bank *B* if the no-monopoly condition does not hold. Consider first that the no-monopoly condition holds. Bank *A* herds if its expected profit in the biased duopoly is higher than in the asymmetric duopoly, $E\Pi_{bD}^A>E\Pi_{aD}^A$. This requires, given that markets are separable, that

$$[\theta_l(1+r_{l,bD}^*)-(1+r+c)]L_{l,bD}^{A*}>[\theta_l(1+r_{l,aD}^*)-(1+r+c)]L_{l,aD}^{A*}, \tag{A29}$$

but (A29) can be rearranged as

$$\theta_l > \frac{(1+r+c)(L^{A*}_{l,bD} - L^{A*}_{l,aD})}{(1+r^*_{l,bD})L^{A*}_{l,bD} - (1+r^*_{l,aD})L^{A*}_{l,aD}} \tag{A30}$$

provided that the denominator of (A30) is positive.[276] We may expand (A30) by substituting (A9), (A11), (A15) and (A16) for the volumes of loans granted in equilibrium and the corresponding market-clearing interest rates. This allows obtain $\theta_l > \frac{6\beta(1+r+c)\theta_l\theta_l^O}{(\alpha+\beta)\theta_l\theta_l^O + \beta(1+r+c)(3\theta_l + 2\theta_l^O)}$.

Consider now that the no-monopoly condition does not hold. Bank *A* herds if its expected profit in the biased duopoly is higher than in the monopoly formed by bank *B*, $E\Pi^A_{bD} > E\Pi^A_M$. This condition, given that markets are separable, implies that

$$[\theta_l(1+r^*_{l,bD}) - (1+r+c)]L^{A*}_{l,bD} > 0. \tag{A31}$$

Rearranging (A31) we have $\theta_l > \frac{(1+r+c)}{1+r^*_{l,bD}}$, which may be extended, by substituting (A16), to obtain

$$\theta_l^{\mathrm{T}} = \frac{3\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + 2\beta(1+r+c)}. \tag{A32}$$

Finally, comparing (A32) and the no-monopoly condition $\theta_l^{\mathrm{M}} = \frac{2\beta(1+r+c)\theta_l^O}{(\alpha+\beta)\theta_l^O + \beta(1+r+c)}$, it is easy to check that $\theta_l^{\mathrm{T}} > \theta_l^{\mathrm{M}}$ provided that $\alpha > \frac{\beta(1+r+c-\theta_l^O)}{\theta_l^O}$, i.e. provided that Assumption 2 is satisfied. Consequently, the herding condition $\theta_l > \theta_l^{\mathrm{T}}$ is not satisfied when the no-monopoly condition does not hold. Hence, when the asymmetric market is a monopoly, i.e. bank *A* does not herd, such market structure is always the equilibrium configuration. This completes the proof of the lemma. ■

Proof of Proposition 1. It follows directly from Lemmas 2 and 3. ■

Proof of Remark 1. It follows from Lemma 1 and Proposition 1. ■

Proof of Lemma 4. Since there will be no herding when the no-monopoly condition is not satisfied (see Lemma 3), we shall only focus on a market where the possible asymmetric configuration is a duopoly. Consider first the case of a rational and an overconfident bank. The threshold level that makes an unbiased bank indifferent to herd is $\theta_l^T = \frac{6\beta(1+r+c)\cdot\theta_l\,\theta_l^O}{(\alpha+\beta)\theta_l\,\theta_l^O + \beta(1+r+c)(3\theta_l + 2\theta_l^O)}$. We may calculate the required bias for an unbiased bank not to herd

[276] By using (A9), (A11), (A15) and (A16) we may expand the expression $(1+r^*_{l,bD})L^{A*}_{l,bD} - (1+r^*_{l,aD})L^{A*}_{l,aD}$ to get $\frac{\beta(1+r+c)^2[2(\theta_l^O)^2 + \theta_l^O\theta_l - 3(\theta_l)^2] + (\alpha+\beta)(1+r+c)\theta_l^O\theta_l(\theta_l^O - \theta_l)}{9(\theta_l)^2(\theta_l^O)^2}$, which is positive for $\theta_l < \theta_l^O < 1$.

(for tractability it is better to express it as a ratio θ_l^O / θ_l^T) such that it yields $\frac{\theta_l^O}{\theta_l^T} = \frac{(\alpha+\beta)\theta_l \, \theta_l^O + \beta(1+r+c)(3\theta_l + 2\theta_l^O)}{6\beta(1+r+c)\theta_l}$

which may be rearranged to

$$\frac{\theta_l^O}{\theta_l^T} = \frac{1}{2} + \frac{\alpha\theta_l^O}{6\beta(1+r+c)} + \frac{\theta_l^O}{6(1+r+c)} + \frac{\theta_l^O}{3\theta_l}. \qquad \text{(A33)}$$

Clearly, the required bias for an unbiased bank not to herd is increasing in α (and obviously in θ_l^O), and decreasing in θ_l , β, *r* and *c*.

For a duopoly of a rational and an underconfident bank we proceed similarly. The threshold level that makes an underconfident bank indifferent to herd is $\theta_l^{UT} = \frac{6\beta(1+r+c)\theta_l \, \theta_l^U}{(\alpha+\beta)\theta_l \, \theta_l^U + \beta(1+r+c)(3\theta_l^U + 2\theta_l)}$. We may calculate the required bias for the biased bank not to herd as $\frac{\theta_l}{\theta_l^{UT}} = \frac{(\alpha+\beta)\theta_l + \beta(1+r+c)(3\theta_l^U + 2\theta_l)}{6\beta(1+r+c)\theta_l^U}$ which may be rearranged to

$$\frac{\theta_l}{\theta_l^{UT}} = \frac{1}{2} + \frac{\alpha\theta_l}{6\beta(1+r+c)} + \frac{\theta_l}{6(1+r+c)} + \frac{\theta_l}{3\theta_l^U}. \qquad \text{(A34)}$$

Clearly, the required bias for the biased bank not to herd is increasing in α and θ_l , and decreasing in β, *r*, *c* and, obviously, θ_l^U . ■

SUPPLEMENTARY MATERIAL

Participation form (blank sample)

FORMULARIO PARTICIPACIÓN
Experimento Tese Doutoral – UDC 2013

TESE DOUTORAL

- Título: Behavioral Microfoundations of Retail Credit Markets
- Autor: David Peón Pose

EXPERIMENTO

- Obxecto: Obter información acerca da toma de decisións nun contexto de incerteza e risco
- Contido: xogo de Trivial + cuestionario perfil de risco + xogo de estratexia
- Duración estimada: 2 horas máximo
- Gratificacións aos participantes no experimento:
  - Convite a café ou refresco
  - Premio de 60 eur ao gañador do xogo de estratexia

LUGAR, DATA E HORA

- Lugar: Aula de informática 0.2 – planta baixa, Facultade de Economía e Empresa, FEE
- Data e hora:
  - SESIÓN 1 - **XOVES 10 DE OUTUBRO, 11:50h**

(recibiredes toda a información por e-mail)

LISTAXE DE ALUMNOS QUE SE COMPROMETEN A PARTICIPAR NO EXPERIMENTO (1/2)

	NOME	Grupo	E-MAIL	Sinatura
1				
2				
3				
4 5 6				
7				
8				
9 10				
11				
12				
13				
14 15				
16				
17				
18 19 20				

Identification form (blank sample)

FORMULARIO IDENTIFICACIÓN

TESE DOUTORAL

- Behavioral Microfoundations of Retail Credit Markets - Autor: David Peón Pose

SESIÓN 1

- Lugar: Aula de informática 0.2 – planta baixa, Facultade de Economía e Empresa, FEE
  - Data e hora: **XOVES 10 DE OUTUBRO, 11:50h**

IMPORTANTE

Toda a información obtida neste experimento será tratada de maneira completamente **anónima e confidencial**

LISTAXE DE ALUMNOS PARTICIPANTES NO EXPERIMENTO (1/2)

	FICHEIRO	NOME	NIF	Sinatura
1	1.			
2	1.			
3	1.			
4	1.			
5	1.			
6	1.			
7	1.			
8	1.			
9	1.			
10	1.			
11	1.			
12	1.			
13	1.			
14	1.			
15	1.			
16	1.			
17	1.			
18	1.			
19	1.			
20	1.			
21	1.			
22	1.			

Individual consent form (LOPD)

FORMULARIO DE CONSENTIMENTO

DATOS DO RESPONSABLE DA RECOLLIDA E CUSTODIA DE DATOS

Nome	David Olegario Peón Pose
NIF / CIF	44.078.038-X
Domicilio	Facultade Economía e Empresa, Universidade da Coruña, UDC Dpto. Economía Financeira e Contabilidade, Despacho 117B Campus de Elviña, s/n – 15071 A Coruña
E-mail	david.peon@udc.es

DESCRIPCIÓN DO EXPERIMENTO E FINALIDADE DOS DATOS PERSOAIS RECABADOS NO MESMO

O experimento no que vai participar é de carácter científico, desenvolvido no marco da Universidade da Coruña, UDC, coa finalidade de obter información para o desenvolvemento da tese de doutoramento

Behavioral Microfoundations of Retail Credit Markets

por David Olegario Peón Pose, dirixida polos Profesores Doutores Anxo Calvo Silvosa (UDC) e Manel Antelo Suárez (USC). O obxecto do experimento é obter información acerca da toma de decisións nun contexto de incerteza e risco. A tal efecto, requeriráse do interesado facilitar información de carácter persoal (sexo, idade, nivel de estudos, perfil de risco financeiro, etc.) do tipo contemplado na LOPD.

INFORMACIÓN RELEVANTE PARA O INTERESADO

En virtude da *Ley Orgánica 15/1999 de Protección de Datos de Carácter Personal*, que ten por obxecto garantir e protexer, no relacionado ao tratamento dos datos persoais, as liberdades e dereitos fundamentais das persoas físicas, especialmente o seu honor e intimidade persoal, infórmase ao interesado e abaixo asinante, como participante no experimento arriba descrito, do seguinte:

- Que o experimento ten finalidade exclusivamente académica e científica, nunca comercial;
- Que os datos recollidos serán tratados de maneira completamente anónima e confidencial;
- Que o obxecto da recollida de datos e realizar unha análise estatística dos datos agregados, de xeito que nunca se publicarán datos a nivel individual dos participantes no experimento;
- Que ningún dos datos recabados no experimento entran dentro da categoría de "datos especialmente protexidos" recollidos no Artigo 7 da devandita Ley;
- Que, de conformidade có Artigo 11 da mesma Ley, o interesado autoriza a eventual cesión a terceiros dos mesmos datos, con finalidade sempre exclusivamente académica e/ou científica, nunca comercial, garantindo en todo momento as cláusulas de anonimato e confidencialidade;
- Que o responsable garda copia, en documento aparte, da relación "ficheiro de datos – datos do interesado" que permita, caso de ser requerido por tribunais de avaliación, revistas académicas, etc., o contacto persoal có interesado a efectos de contrastar a súa efectiva participación no experimento.

O abaixo asinante dá a súa conformidade á participación no experimento e ao tratamento dos datos cedidos ao responsable do mesmo, conforme aos termos descritos no presente formulario de consentimento.

A Coruña, __ de ___________ de 2013

NOME ______________________________

RESUMO EN GALEGO

A crise financeira global dos anos 2007 e 2008 e a crise de débeda pública que lle sucedeu na zona Euro persuadiu a académicos e autoridades para revisar os nosos coñecementos acerca do funcionamento das economías de mercado. Entre os temas revisados salientamos a natureza dos ciclos económicos, a efectividade das políticas monetarias, o papel xogado polos derivados financeiros, ou a efectividade da regulación bancaria. Con todo, o factor ao que se lle ten prestado máis atención é, quizais, o crédito.

O recente episodio anovou o interese no papel que o crédito xoga na economía, traendo a primeira liña clásicos como Charles Kindleberger ou Hyman Minsky, entre outros. De feito, o bo comportamento das economías occidentais antes da Gran Recesión foi consecuencia en boa medida dos niveis de endebedamento asumidos. O exceso de confianza podería ter provocado a crenza, por parte dos axentes económicos, de que esta vez era diferente e que os bos tempos haberían durar sempre. Os riscos percibidos minorarían, ao que lle sucedería un maior apancamento financeiro. Así, a ratio de pasivos financeiros sobre PIB entre 1995 e 2007 aumentou en países como o Reino Unido desde o 128% ao 213%, e as burbullas inmobiliarias sucedéronse en países tan distantes como os Estados Unidos, Irlanda, España, Rusia, Singapur, China ou os Emiratos Árabes. Burbullas todas elas que colapsarían co estoupido da crise financeira.

Nas economías onde o peso do sector bancario non é moi relevante, a ratio de crédito bancario sobre PIB tende a permanecer baixo ao longo do ciclo económico. Por exemplo, nos EE.UU. entre os anos 50 a 1995, a ratio oscilou entre o 7% e o 14% (Himmelberg e Morgan, 1995). Nos sistemas bancarios, pola contra, esta ratio é a miúdo moito máis alta e medrou de maneira agresiva durante a pasada crise. En España, por exemplo, a mediados dos anos 90 a ratio oscilaba no 60%, para dispararse ata o 175% en 2009. O crédito concedido polo sector bancario español ás economías domésticas e empresas entre 1995 e 2008 pasou dos 271.000 millóns aos 1.870.000 millóns de euros , case sete veces máis. Durante o mesmo período, o PIB medrou un 58%. Por outra banda, a análise histórica dos episodios de crise financeira internacional por parte de Reinhart e Rogoff (2011) confirma dous feitos adicionais. Primeiro, o aumento das débedas privadas é un precedente recorrente das crises bancarias. Tomando de novo o exemplo español, en decembro de 2007 só o 0,93% dos créditos concedidos a economías domésticas e empresas figuraban como impagados; en xaneiro de 2014, a cifra ascendía ao 13,58%. En cambio, en países máis orientados aos sistemas financeiros de mercado, como EE.UU., só se observaban cifras similares en tarxetas de crédito e préstamos universitarios. En hipotecas e créditos para compra de automóbil, a morosidade apenas excedía o 5%. O segundo feito constatado é que as crises bancarias a miúdo preceden (e predín) as crises de débeda soberana. O nexo foi palpable na recente crise da Eurozona e o efecto realimentación entre débeda pública e o balance dos bancos. Por tanto, as crises bancarias que seguen a períodos de políticas de crédito laxas non só teñen consecuencias prexudiciais sobre a estabilidade do sector bancario, senón tamén sobre toda a economía.

Por tanto, analizar a eficiencia do sector bancario na concesión de crédito á economía revélase como un campo de investigación ben interesante. A seguir, resumimos o principal obxecto da tese, así como o enfoque seguido na nosa investigación. Primeiro, determinamos o obxecto de estudo. Segundo, enumeramos os principais obxectivos perseguidos. Terceiro, a metodoloxía implementada. Por último, describimos a estrutura da tese e resumimos os contidos de cada capítulo.

Obxecto de estudo

Xa que as crises de crédito poden asociarse tanto con efectos desde o lado da oferta como da demanda, debemos clarificar de inicio que a presente tese doutoral pon o seu foco no lado da oferta, ao obxecto de proporcionar un medio alternativo de análise das causas tras un boom de crédito.

Así, o obxecto de estudo desta tese é a eficiencia dos sistemas financeiros bancarios á hora de conceder crédito á economía. En consecuencia, o ámbito da investigación son os mercados de crédito polo miúdo, definidos como as transaccións entre banca comercial e os seus clientes que inclúa a concesión dalgún tipo de crédito (préstamos, hipotecas, etc.) financiado, principalmente, cós depósitos doutros clientes. A principal innovación é o marco conceptual que empregamos a tal efecto: a economía e finanzas do comportamento (*behavioral economics and finance* na terminoloxía inglesa). Nos sistemas financeiros de mercado, o enfoque habitual de análise da eficiencia é a Hipótese do Mercado Eficiente (*Efficient Market Hypothesis*, EMH). Porén, veremos que a competencia imperfecta e as asimetrías de información características dos sistemas bancarios deixan a EMH sen contido neste ámbito. A primeira contribución desta tese é proporcionar un enfoque behaviorista ou conductual para analizar a eficiencia dos sistemas bancarios, o que permitiría explicar o xeito no que os nesgos de comportamento dos participantes na industria bancaria poderían explicar os ciclos de crédito.

Esa é en efecto a principal cuestión que se pretende respostar: podería ser que as burbullas crediticias fosen unha manifestación dun comportamento rabaño a consecuencia dos distintos nesgos de comportamento dos executivos e empregados na industria? Entendemos que esta é unha cuestión relevante que merece ser respostada. As investigacións académicas posteriores á recente crise financeira teñen analizado aspectos como o papel dos incentivos, as titulizacións ou o risco moral, pero pouco se ten feito por interpretar o papel que a psicoloxía humana podería ter xogado. Non deixa de ser curioso: a *behavioral economics* ten identificado e explicado un feixe de anomalías en areas tan diversas como a saúde, a educación, a enerxía, os seguros ou as políticas públicas. A área de máis éxito é, de feito, a *behavioral finance* aplicada aos mercados financeiros.

Por tanto, suxerimos ampliar a economía e finanzas do comportamento ao análise da eficiencia informativa nos mercados bancarios. Este enfoque complementaría a literatura sobre burbullas de crédito, suxerindo que os efectos do risco moral e dos incentivos poderían ter sido máis prexudiciais debido aos nesgos de comportamento. Asemade, contribuiría ao debate aberto acerca da necesidade de mellorar a regulación macroprudencial (Brunnermeier et al., 2009) ou os pros e contras de separar as funcións monetarias e de crédito mediante un sistema bancario de reserva total (Benes e Kumhof, 2012).

Obxectivos

O obxectivo fundamental desta tese é a análise da eficiencia informativa dos mercados de crédito polo miúdo mediante un enfoque behaviorista. A principal motivación é proporcionar unha xustificación que explique como distintos nesgos de comportamento polos participantes na industria bancaria podería provocar unha concesión de crédito excesiva polos bancos comerciais e un comportamento gregario entre eles. Tal obxectivo fundamental pode ser debullado nunha serie de obxectivos específicos.

Primeiro, preténdese revisar os principais marcos conceptuais que teñen sido empregados para analizar a eficiencia informativa dos mercados financeiros en xeral, e do sector bancario en particular. Nese ámbito, interpretamos asemade os obstáculos que limitan a aplicación do enfoque clásico nos mercados financeiros, a EMH, ao sistema bancario. Segundo, revisamos en detalle a economía e finanzas do comportamento como marco conceptual da nosa investigación teórica e experimental. Terceiro, imos na procura dun enfoque alternativo que permita testar a eficiencia informativa dos mercados de crédito polo miúdo dun xeito similar ao que se interpreta no ámbito da EMH. Dito enfoque alternativo segue a literatura conductual no ámbito dos mercados financeiros, pero salvando a presencia de asimetrías de información e competencia imperfecta que impiden a extensión da EMH aos sistemas bancarios.

Cuarto, buscamos proporcionar evidencia experimental dos efectos que os nesgos psicolóxicos poderían ter sobre as políticas de crédito que establecen os bancos. Respecto aos nesgos, centrámonos en dúas áreas da literatura conductual: os distintos perfís de risco conforme a *prospect theory*, e o exceso de confianza (overconfidence). A respecto das políticas de crédito, medimos os efectos en termos de prezos, volumes e calidade o crédito. Quinto, preténdese proporcionar un modelo teórico que explique o comportamento de bancos de distinta natureza, uns dirixidos por executivos optimistas de máis e outros racionais, cando compiten por proporcionar crédito a clientes. Entre as preguntas que se pretenden responder están por que e cando os bancos racionais estarían dispostos a imitar aos seus nesgados competidores, os efectos que os nesgos inducirían na competencia bancaria ao longo do ciclo económico, ou as leccións a extraer para o debate por unha regulación macroprudencial mellorada.

Metodoloxía

Buscamos establecer se existe xustificación pola que a psicoloxía humana —en particular, diferentes nesgos de comportamento dos participantes na industria bancaria— explique un comportamento rabaño que amplifique os auxes e caídas dos ciclos de crédito. Procedemos como segue. Primeiro, identificamos os marcos conceptuais da literatura que poderían contribuír ao noso traballo. Estas son as teorías de crédito e eficiencia do sector bancario, a hipótese do mercado eficiente, que é o paradigma clásico para testar a eficiencia dos mercados financeiros, e a *behavioral finance*, a área de maior éxito á hora de proporcionar unha interpretación alternativa á EMH nos mercados financeiros.

Segundo, centrámonos na *behavioral finance* como marco conceptual da nosa investigación. Así pois, revisamos os principais nesgos e anomalías identificados na literatura, con especial atención a dúas áreas de investigación: *prospect theory* e *overconfidence*.

Terceiro, introducimos un enfoque behaviorista ao obxecto de analizar a eficiencia informativa dos mercados de crédito polo miúdo. Isto require unicamente aplicar o enfoque clásico, resumido por Shleifer (2000), no que a *behavioral finance* analiza a eficiencia informativa dos mercados financeiros. A tal efecto, debatemos primeiro as condicións nas que este enfoque sería válido no ámbito dos mercados bancarios. Satisfeitas as condicións, o enfoque conductual consistiría nun procedemento en tres etapas: identificar se os participantes na industria mostran nesgos que poderían conformar un sentimento de mercado, comprobar se o sentimento de mercado podería exhibir tendencias ou patróns predicibles, e identificar os límites ao arbitraxe nos mercados de crédito polo miúdo.

Cuarto, no cerne desta tese, proporcionamos un enfoque teórico e experimental para respostar as preguntas das tres etapas. En concreto, desenvolvemos unha investigación experimental para testar o primeiro paso, e ofrecemos un modelo teórico que explica de que xeito o comportamento rabaño entre bancos racionais e nesgados induciría un sentimento de mercado ao longo do ciclo, e cales serían os límites ao arbitraxe que operan na industria e impiden restablecer a súa eficiencia.

A investigación experimental consta de dous tipos de tests: por unha banda, uns cuestionarios deseñados para establecer o perfil psicolóxico, en termos de *prospect theory* e *overconfidence*, de cada participante; por outra, un xogo de simulación de negocios que replica, nun entorno experimental, o xeito no que os bancos outorgan crédito aos seus potenciais clientes, ao obxecto de obter información sobre volume de crédito e prezo que cada xogador estaría disposto a ofertar, en condicións de incerteza e risco. En total, 126 estudantes de grao e posgrao da Universidade da Coruña (UDC) completaron ambos tests, o cal permite establecer a conexión entre os seus perfís de comportamento e as súas actitudes ante o risco no xogo. Estruturamos esta premisa básica nunha serie de hipóteses a testar. As técnicas estatísticas empregadas a tal efecto inclúen estatística univariada (tests de normalidade, rango intercuartil, etc.), bivariada (correlacións, ANOVAs, regresións), e multivariante: regresión lineal múltiple (MLR), análise de compoñentes principais (PCA), análise clúster e análise de correspondencias.

As etapas dúas e tres no enfoque conductual son abordadas mediante un modelo teórico: construímos un modelo simple de competencia duopolística entre bancos de distinta natureza que mostra de que xeito os bancos racionais seguirían aos seus nesgados competidores, concedendo excesivo crédito en contextos de auxe económico. O modelo predí que os bancos nesgados liderarían o sector e os racionais os imitarían en determinadas condicións, que derivamos. Logo, describimos os límites ao arbitraxe implícitos no modelo. Por último, ofrecemos unha dinamización do modelo para aportar unha intuición da amplificación do ciclo de crédito producido pola competencia entre bancos.

Estrutura da tese

Os contidos principais da tese se presentan en tres partes máis un resumo dos principais resultados e unha serie de conclusións, seguido polas referencias bibliográficas e apéndices.

A **Parte I** está formada por tres capítulos. O Capitulo 1 define os mercados de crédito polo miúdo e segue coas principais teorías de crédito e eficiencia bancaria. A revisión das distintas teorías e conceptos de eficiencia económica do sector bancario ilustra como este enfoque difire do xeito no que se interpreta a eficiencia no contexto dos mercados financeiros. Isto abórdase no Capítulo 2, que describe os fundamentos teóricos da EMH. Por último, o Capítulo 3 introduce os fundamentos da *behavioral finance*. Fronte aos postulados de expectativas racionais e mercado eficiente das finanzas estándar, a economía do comportamento suxire en cambio un enfoque máis amplo baseado na combinación de distintas ciencias sociais, incluídas a psicoloxía, a socioloxía ou a demografía.

A **Parte II** está formada por dous capítulos, ambos dedicados a proporcionar un coñecemento en profundidade de diversos ámbitos da *behavioral finance* que resultarán esenciais na investigación teórica e experimental da tese. O capítulo 4 presenta unha taxonomía orixinal e revisa en profundidade os nesgos e anomalías máis significativos na literatura do comportamento. O obxectivo será seleccionar dúas áreas nas que centrar a nosa análise en Parte III. O Capítulo 5 revisa ditas áreas de maneira máis extensa, *overconfidence* e *prospect theory*. En primeira instancia xustificamos a nosa escolla: son dúas áreas relevantes e moi estudiadas dentro da *behavioral finance*, ambos conceptos teñen sido empregados para explicar distintos comportamentos agresivos polos investidores, e poderían así mesmo explicar como os erros de percepción dos participantes no sector bancario poderían inducilos a proporcionar políticas de crédito pouco sólidas. Logo, poñemos o foco en diversos aspectos que serán precisos na investigación experimental na Parte III —en particular, as distintas medidas dispoñibles e o xeito de calibrar os parámetros básicos a nivel individual a través dunha serie de cuestionarios.

A **Parte III** está destinada a proporcionar unha xustificación pola que a psicoloxía humana desafiaría a eficiencia nos sistemas bancarios. A análise preséntase en tres etapas, dividida en catro capítulos. O Capítulo 6 introduce unha alternativa para analizar a eficiencia dos sistemas financeiros bancarios. O enfoque, en tres etapas, analiza unicamente o aspecto da EMH referido á eficiencia informativa e é válido só para o mercado de crédito no seu conxunto. A investigación experimental dos Capítulos 7 e 8 busca testar a primeira das etapas. En concreto, centrámonos nos efectos da *prospect* *theory* e o exceso de confianza. Primeiro, o Capítulo 7 busca detectar a existencia destes nesgos entre unha serie de participantes nun experimento. Segundo, o Capítulo 8 busca recoñecer se estes nesgos poderían alimentar, entre o mesmo grupo de participantes, un comportamento propenso ao risco nun mercado simulado de crédito. As sesións experimentais tiveron lugar na Facultade de Economía e Empresa da UDC en outubro de 2013, participando un total de 126 estudantes de grao e posgrao da UDC.

Por último, o Capítulo 9 proporciona un modelo teórico que segue a segunda e terceira etapas do método conductual para determinar o xeito no que os bancos compiten para dar crédito. O modelo parte do suposto de que algúns bancos na industria estarían nesgados en termos de confianza e optimismo excesivos —en particular, durante os anos de bonanza do ciclo económico. Así, construímos un modelo de competencia duopolística entre bancos para mostrar que os nesgos psicolóxicos dos participantes no sector serían suficientes para explicar como se amplifican as burbullas crediticias. Logo, estendemos o modelo para explicar o xeito no que o ciclo do crédito se amplifica debido á competencia entre bancos. Obtemos que o pesimismo non é unha explicación da etapa recesiva do ciclo; pola contra, é a euforia durante períodos prolongados de bonanza o que sementaría a subseguinte caída. Por último, ofrecemos unha dinamización do modelo para profundar na comprensión de como a competencia entre bancos, algúns de racionalidade limitada, amplificarían o ciclo crediticio. Deste xeito, o modelo realiza algunhas predicións consistentes coa observación empírica —en particular, que os efectos dos nesgos son máis graves durante a fase alcista do ciclo e canto menor sexa a calidade crediticia do nicho de mercado.

Principais resultados e conclusións. A tese remata coa divulgación dos resultados principais que se extraen do traballo, así como cunha serie de conclusións e suxestións para futura investigación. En conxunto, as investigacións desta tese poderían ser unha contribución relevante para identificar as posibles eivas do sector bancario, ao obxecto de promover normativas complementarias —en particular sobre regulación macroprudencial e o papel dos bancos centrais. O noso modelo mostraría de que xeito os nesgos de comportamento poderían guiar os mercados de crédito polo miúdo e por que os límites ao arbitraxe implicarían que os sistemas financeiros bancarios tenderían a ser menos eficientes, no senso informacional, que os sistemas de mercado. Con todo, a solución non é máis regulación per se, senón mellor regulación. Por exemplo, o enfoque conductual que empregamos suxeriría as bondades dunha regulación contracíclica; como levala a cabo, porén, vai máis aló do ámbito desta tese. Máis aínda, debemos ter presente a posibilidade de que as autoridades económicas, do mesmo xeito que acontece cós bancos, poidan errar no seu propósito de aplicar as necesarias políticas de contrapeso.

RESUMEN EN CASTELLANO

La crisis financiera global de los años 2007 y 2008 y la crisis de la deuda pública que le sucedió han persuadido a académicos y autoridades para revisar nuestros conocimientos sobre el funcionamiento de las economías de mercado. Entre los temas revisados cabe destacar la naturaleza de los ciclos económicos, la eficacia de la política monetaria, el papel desempeñado por los derivados financieros, o la efectividad de la regulación bancaria. Sin embargo, el factor al que se le ha prestado más atención es, tal vez, el crédito. El episodio renovó el interés en el papel que juega el crédito en la economía, trayendo a primera línea clásicos como Charles Kindleberger y Hyman Minsky, entre otros. De hecho, el buen comportamiento de las economías occidentales antes de la Gran Recesión fue en gran parte resultado de los niveles de endeudamiento asumidos.

El exceso de confianza podría haber provocado la creencia, por parte de los agentes económicos, de que esta vez era diferente y que los buenos tiempos durarían para siempre. Los riesgos percibidos minorarían, a lo que le seguiría un mayor apalancamiento financiero. La proporción de los pasivos financieros sobre PIB entre 1995 y 2007 aumentó en países como el Reino Unido de 128% a 213%, y las burbujas inmobiliarias se sucedieron en países tan lejanos como los Estados Unidos, Irlanda, España, Rusia, Singapur, China o los Emiratos Árabes. Burbujas que colapsarían con el estallido de la crisis financiera. En las economías donde el peso del sector bancario no es muy relevante, la proporción de crédito bancario sobre PIB tiende a permanecer bajo en diferentes momentos del ciclo económico. Por ejemplo, en los EE.UU. entre los años 50 y 1995, la proporción fluctuó entre el 7% y el 14% (Himmelberg y Morgan, 1995). En los sistemas bancarios, sin embargo, esta relación es a menudo mucho más alta y creció agresivamente durante la última crisis. En España, por ejemplo, a mediados de los 90 la ratio osciló en niveles del 60%, para dispararse hasta el 175% en 2009. El crédito otorgado por el sector bancario español a las economías domésticas y empresas entre 1995 y 2008 pasó de 271.000 a 1.870.000 millones, casi siete veces más. Durante el mismo período, el PIB creció un 58%.

Por otra parte, el análisis histórico de los episodios de crisis financiera mundial por Reinhart y Rogoff (2011) confirma dos hechos adicionales. Primero, el aumento de las deudas privadas es un precedente recurrente de las crisis bancarias. Tomando de nuevo el ejemplo de España, en diciembre de 2007 sólo el 0,93% de los préstamos concedidos a las economías domésticas y empresas figuraban como impagados; en enero de 2014, la cifra se situaba en el 13,58%. En países más orientados a sistemas de mercado, como EE.UU., sólo se observaban cifras similares en tarjetas de crédito y préstamos universitarios. En hipotecas y préstamos para compra de coche, la morosidad apenas excedía el 5%. El segundo hecho es que las crisis bancarias a menudo preceden (y predicen) las crisis de deuda soberana. El nexo fue evidente en la reciente crisis de la zona euro y el efecto de retroalimentación entre deuda pública y el balance de los bancos. Por lo tanto, las crisis bancarias que siguen tras períodos de políticas crediticias laxas no sólo tienen consecuencias perjudiciales para la estabilidad del sector bancario, sino también sobre la economía en su conjunto.

Por tanto, analizar la eficiencia del sector bancario al conceder crédito a la economía se revela como un campo de investigación interesante. A continuación, resumimos el objeto principal de la tesis, así como el enfoque seguido en nuestra investigación. Primero, determinamos el objeto de estudio. Segundo, enumeramos los objetivos principales que se persiguen. Tercero, la metodología empleada. Por último, se describe la estructura de la tesis y resumimos los contenidos de cada capítulo.

Objeto de estudio

Dado que las crisis de crédito pueden asociarse tanto con efectos desde el lado de la oferta como de la demanda, debemos aclarar que esta tesis pone su foco en el lado de la oferta, con el fin de proporcionar un medio alternativo de análisis de las causas detrás de un auge del crédito.

Así, el objeto de estudio de esta tesis es la eficiencia de los sistemas financieros bancarios en la concesión de crédito a la economía. En consecuencia, el alcance de nuestra investigación son los mercados de crédito minorista, definidos como las transacciones entre los bancos comerciales y sus clientes que incluyan la concesión de algún tipo de crédito (préstamos, hipotecas, etc) financiados, en su mayor parte, con los depósitos de otros clientes. La principal innovación es el marco conceptual que utilizamos para este fin: la economía y las finanzas del comportamiento (*behavioral economics and finance* en su terminología en inglés). En los sistemas financieros de mercado, el enfoque habitual de análisis de la eficiencia es la Hipótesis del Mercado Eficiente (*Efficient Market Hypothesis*, EMH). Sin embargo, la competencia imperfecta y las asimetrías de información características de los sistemas bancarios dejan la EMH sin contenido en este ámbito. Nuestra primera contribución es proporcionar un enfoque behaviorista para analizar la eficiencia de los sistemas bancarios, lo que explicaría cómo los sesgos de comportamiento de los participantes en la industria podrían explicar los ciclos de crédito.

Esta es efectivamente la principal pregunta que queremos responder: ¿podría ser que las burbujas de crédito alimentadas por el sector bancario fuesen una manifestación del comportamiento de rebaño, como resultado de los distintos sesgos de comportamiento de los ejecutivos y empleados de la industria? Entendemos que esta es una cuestión relevante que merece ser contestada. Las investigaciones tras la reciente crisis financiera han analizado aspectos como el papel de los incentivos, las titulizaciones o el riesgo moral, pero poco se ha hecho por interpretar el papel que la psicología humana podría haber jugado. No deja de ser curioso: la *behavioral economics* ha identificado y explicado un buen número de anomalías en campos tan diversos como la salud, la educación, la energía, los seguros o las políticas públicas. El área de más éxito es, de hecho, la *behavioral finance* aplicada a los mercados financieros. Por tanto, sugerimos ampliar las finanzas del comportamiento al análisis de la eficiencia informativa en los mercados bancarios. Este enfoque complementaría la literatura sobre burbujas de crédito, sugiriendo que los efectos del riesgo moral y los incentivos podrían ser más perjudiciales debido a los sesgos de comportamiento. Así mismo, contribuiría al debate abierto sobre la necesidad de mejorar la regulación macroprudencial (Brunnermeier et al., 2009) o los pros y contras de separar las funciones monetarias y de crédito mediante un sistema bancario de reserva total (Benes y Kumhof 2012).

Objetivos

El objetivo principal de esta tesis es el análisis de la eficiencia informativa de los mercados de crédito minorista a través de un enfoque conductista. La motivación principal es proporcionar una justificación que explique cómo distintos sesgos de comportamiento de los participantes en el sector bancario podría generar una concesión de crédito excesiva por los bancos comerciales y un comportamiento gregario entre ellos. Tal objetivo fundamental puede ser diseccionado en una serie de objetivos específicos.

En primer lugar, se pretende revisar los principales marcos conceptuales utilizados para analizar la eficiencia informativa de los mercados financieros en general, y del sector bancario en particular. En ese ámbito, interpretamos asimismo los obstáculos que limitan la aplicación del enfoque clásico en los mercados financieros, la EMH, al sistema bancario. En segundo lugar, revisamos de forma exhaustiva la economía y las finanzas del comportamiento como marco conceptual de nuestra investigación teórica y experimental. En tercer lugar, buscamos un enfoque alternativo que permita testar la eficiencia informativa de los mercados de crédito minorista de una forma similar a la que se interpreta la eficiencia en el ámbito de la EMH. Dicho enfoque alternativo sigue la literatura behaviorista en el ámbito de los mercados financieros, pero salvando la presencia de asimetrías de información y competencia imperfecta que impiden la extensión de la EMH a los sistemas bancarios.

En cuarto lugar, buscamos proporcionar evidencia experimental de los efectos que los sesgos psicológicos podrían tener sobre las políticas de crédito bancario. En cuanto a los sesgos, nos centramos en dos áreas relevantes de la literatura conductual: los diferentes perfiles de riesgo de acuerdo con la *prospect theory*, y el exceso de confianza (*overconfidence*). Con respecto a las políticas de préstamo, se miden los efectos en términos de precios, volúmenes y la calidad del crédito. En quinto lugar, se pretende proporcionar un modelo teórico que explique el comportamiento de bancos de diferente naturaleza, unos dirigidos por ejecutivos excesivamente optimistas y no otros no, cuando compiten por conceder créditos a potenciales clientes. Entre las preguntas que queremos responder están el por qué y cuando los bancos racionales estarían dispuestos a imitar a sus sesgados competidores, los efectos que los sesgos inducirían en la competencia bancaria a lo largo del ciclo económico, o las lecciones que se pueden extraer para el debate por una mejor regulación macroprudencial.

Metodología

Buscamos establecer si existe justificación para que la psicología humana —en particular, diferentes sesgos de comportamiento de los participantes en el sector bancario— explique un comportamiento de rebaño que amplifique los auges y caídas del crédito. Procedemos de la siguiente manera. Primero, identificamos los marcos conceptuales que podrían contribuir a nuestro trabajo. Estas son las teorías de crédito y eficiencia del sector bancario, la hipótesis del mercado eficiente, que es el paradigma clásico para testar la eficiencia de los mercados financieros, y la *behavioral finance*, el área de mayor éxito a la hora de proporcionar una interpretación alternativa a la EMH en los mercados financieros. Segundo, nos centramos en la *behavioral finance* como marco conceptual de nuestra investigación. Así, revisamos los principales sesgos y anomalías identificados en la literatura, con especial atención a dos áreas de investigación: *prospect theory* y *overconfidence*.

Tercero, introducimos un enfoque behaviorista con el fin de analizar la eficiencia informativa de los mercados de crédito minorista. Esto requiere aplicar el enfoque clásico, resumido por Shleifer (2000), por el cual la *behavioral finance* examina la eficiencia informativa de los mercados financieros. Para ello, discutimos primero las condiciones en las que este enfoque sería válido en el ámbito de los mercados bancarios. Cumplidas dichas condiciones, el enfoque conductual consistiría en un método en tres etapas: identificar si los participantes en la industria muestran sesgos que podrían conformar un sentimiento de mercado, comprobar si dicho sentimiento de mercado podría exhibir tendencias o patrones previsibles, e identificar los límites de arbitraje en los mercados de crédito minorista.

Cuarto, en el núcleo de esta tesis, ofrecemos un enfoque teórico y experimental para responder a las preguntas de las tres etapas. En concreto, desarrollamos una investigación experimental para poner a prueba el primer paso, y ofrecemos un modelo teórico que explica cómo el comportamiento de rebaño entre bancos racionales y sesgados induciría un sentimiento de mercado a lo largo del ciclo, y cuáles serían los límites de arbitraje que operan en la industria e impiden reestablecer su eficiencia.

La investigación experimental consta de dos tipos de tests: por un lado, unos cuestionarios diseñados para establecer el perfil psicológico, en términos de *prospect theory* y *overconfidence*, de cada participante; por otro, un juego de simulación de negocios que replica, en un entorno experimental, el contexto en que los bancos dan crédito a sus potenciales clientes, en condiciones de incertidumbre y riesgo. En total, 126 estudiantes de grado y postgrado de la Universidade da Coruña (UDC) completaron ambas pruebas, lo que permite establecer la conexión entre sus perfiles de conducta y sus actitudes hacia el riesgo en el juego. Estructuramos esta premisa básica en una serie de hipótesis a testar. Las técnicas estadísticas utilizadas para este propósito incluyen estadística univariada (pruebas de normalidad, rango intercuartílico, etc.), bivariada (correlaciones, ANOVA, regresiones) y estadística multivariante: regresión lineal múltiple (MLR), análisis de componentes principales (PCA), análisis clúster y análisis de correspondencias.

Las etapas dos y tres en el enfoque conductual se abordan con un modelo teórico: construimos un modelo simple de competencia duopolística entre bancos de distinta naturaleza que muestra cómo los bancos racionales seguirían a sus sesgados competidores, concediendo excesivo crédito en contextos de bonanza económica. El modelo predice que los bancos sesgados liderarían el sector, y los racionales les imitarían en determinadas condiciones, que derivamos. Posteriormente, describimos los límites de arbitraje implícitos en el modelo. Por último, ofrecemos una dinamización del modelo para aportar una intuición de la amplificación del ciclo de crédito producido por la competencia entre bancos.

Estructura de la tesis

Los contenidos principales de la tesis se presentan en tres partes más un resumen de los principales resultados y una serie de conclusiones, seguido por las referencias bibliográficas y apéndices.

La **Parte I** consta de tres capítulos. El Capítulo 1 define los mercados de crédito minorista y continúa con las principales teorías de crédito y eficiencia bancaria. La revisión de las diferentes teorías y conceptos de eficiencia económica del sector bancario ilustra cómo este enfoque se diferencia de la forma en que se interpreta la eficiencia en el contexto de los mercados financieros. Esto se trata en el Capítulo 2, que describe los fundamentos teóricos de la EMH. Por último, el Capítulo 3 introduce los fundamentos de la *behavioral finance*. Frente a los postulados de expectativas racionales y mercado eficiente de las finanzas estándar, la economía del comportamiento sugiere un enfoque más amplio basado en la combinación de ciencias sociales como la psicología, la sociología o la demografía.

La **Parte II** consta de dos capítulos, dedicados a proporcionar un mayor conocimiento de los ámbitos de la *behavioral finance* que resultarán esenciales en la investigación teórica y experimental de la tesis. El Capítulo 4 presenta una taxonomía original y revisa los sesgos y anomalías más importantes. El objetivo es seleccionar dos áreas en las cuales centrar nuestro análisis en la Parte III. El Capítulo 5 revisa en detalle estas áreas, *overconfidence* y *prospect theory*. Primero justificamos nuestra elección: son dos áreas relevantes y muy estudiadas en la *behavioral finance*, ambos conceptos se han utilizado para explicar comportamientos agresivos de los inversionistas, y podrían también explicar cómo los errores de percepción de los participantes en el sector bancario podrían inducirlos a implementar políticas de préstamo poco sólidas. Después, nos centramos en diversos aspectos que serán necesarios en la investigación experimental en la Parte III —en particular, las distintas medidas disponibles y la manera de calibrar los parámetros básicos a nivel individual a través de una serie de cuestionarios.

La **Parte III** está destinada a proporcionar una justificación por la que la psicología humana desafiaría la eficiencia en los sistemas bancarios. El análisis se presenta en tres etapas, dividido en cuatro capítulos. El Capítulo 6 presenta una alternativa para analizar la eficiencia de los sistemas financieros bancarios. El enfoque, en tres etapas, analiza sólo el aspecto de la EMH referido a la eficiencia informativa y es válida únicamente para el mercado de crédito en su conjunto. La investigación experimental de los Capítulos 7 y 8 tiene por objeto testar la primera de las etapas. En concreto, nos centramos en los efectos de la *prospect theory* y el exceso de confianza. En primer lugar, el Capítulo 7 trata de detectar la existencia de estos sesgos entre un grupo de participantes en un experimento. En segundo lugar, el Capítulo 8 busca reconocer si estos sesgos podrían alimentar, entre el mismo grupo de participantes, un comportamiento proclive al riesgo en un mercado de crédito simulado. Las sesiones experimentales se llevaron a cabo en la Facultad de Economía y Empresa de la UDC en octubre de 2013, participando un total de 126 estudiantes de grado y posgrado de la UDC.

Por último, el Capítulo 9 proporciona un modelo teórico que sigue la segunda y tercera etapas del método conductual para determinar la manera en que los bancos compiten por dar crédito. El modelo parte de la hipótesis de que algunos bancos estarían sesgados en términos de confianza y optimismo excesivos —en particular, durante los años de auge del ciclo económico. Elaboramos un modelo de competencia duopolística entre bancos para mostrar que los sesgos psicológicos de los participantes en el sector serían suficientes para explicar cómo se amplifican las burbujas crediticias. Después, extendemos el modelo para explicar cómo el ciclo del crédito se amplifica debido a la competencia entre los bancos. Obtenemos que el pesimismo no es una explicación suficiente de las etapas recesivas del ciclo; al contrario, es la euforia durante periodos prolongados de bonanza los que siembran la caída posterior. Por último, ofrecemos una dinamización del modelo para profundizar en la comprensión de cómo la competencia entre bancos amplificarían el ciclo de crédito. El modelo realiza algunas predicciones consistentes con la observación empírica —en particular, que los efectos de los sesgos son más graves durante la fase alcista del ciclo y cuanto menor sea la calidad crediticia del nicho de mercado.

Principales resultados y conclusiones. La tesis concluye con la divulgación de los principales resultados que se extraen del trabajo, así como una serie de conclusiones y sugerencias para futuras investigaciones. En conjunto, las investigaciones de esta tesis podrían ser una contribución relevante para identificar las posibles taras del sector bancario, con el fin de promover normativas adicionales —en particular, sobre regulación macroprudencial y el papel de los bancos centrales. Nuestro modelo mostraría cómo los sesgos de comportamiento podrían guiar los mercados de crédito minorista y por qué los límites de arbitraje implicarían que los sistemas bancarios tenderían a ser menos eficientes, desde el punto de vista informacional, que los sistemas de mercado. Aún así, la solución no sería más regulación per se, sino una mejor regulación. Así, el enfoque conductual que empleamos sugiere las bondades de una regulación contracíclica; cómo llevarla a cabo, sin embargo, va más allá del alcance de esta tesis. Más aún, hay que tener en cuenta la posibilidad de que las autoridades, al igual que le ocurre a los bancos, puedan errar en su propósito de aplicar las necesarias políticas de contrapeso.