Determinants of investing in innovative activities by agri-food and KIBS firms in rural areas: An exploratory analysis

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Abstract

Using a database on innovation activities by Spanish firms, we perform an exploratory analysis on a frequently overlooked area of research: innovation investment decisions by small firms in rural areas where socio-economic indicators are weak. We focus on two quite different sectors of interest there, agri-food and t-KIBS firms, to explore how the regional context influences the capacity and the nature of innovation. Following the TOE approach as a conceptual framework, we perform a multivariate statistical analysis based on MCA and PCA combined, to identify the most relevant factors among a list of 73 indicators in four broad domains, including innovation decisions as well as organisational, technological and environmental determinants. The exploratory results obtained suggest an open field of research. Thus, we observe a distinctive behaviour of marketing innovation by agri-food firms that is related to former ICT experience, while services innovation by t-KIBS would be related to the objective of entering new market niches. Some results confirm previous results for SMEs outside rural areas, such as financial constraints, lack of qualified personnel, and strong competition being relevant barriers to invest in R & D by t-KIBS firms. Contrariwise, we dispute the assertion that agri-food firms are primarily oriented towards product and process innovation: what comes together is product and organisational innovation.

Keywords: innovation, rural SMEs, R & D investment decisions, agri-food, KIBS, MCA, PCA

JEL Classification: O31, L21, C38.

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1. Introduction

Three quarters of Europe are rural areas where more than half of the population lives. However, growth prospects are sluggish there, due to depopulation and ageing (European Commission, 2013). This is determinant both for firms operating in rural areas – since they have to face a less favourable environment compared to firms in urban areas – as well as in terms of public policies. Following Fernandes et al. (2015), the diversification of productive activities is a key target for rural development policies in Europe since 1997 (European Commission, 1997), and promoting business success is perceived as a key factor in the revitalisation processes for rural European areas (OECD, 2006).

Innovation is a key driver of corporate value for small firms in any sector. Indeed, academics have traced a positive relationship between innovation and superior performance (e.g., Thornhill, 2006). Small firms that do not seek to innovate run the risk of becoming uncompetitive because of obsolete products and processes (Madrid-Guijarro et al., 2009). It is not surprising, therefore, that the policy recommendations for rural development today, by both European authorities – e.g., the Framework Programme for Research and Innovation – Horizon 2020 (European Commission, 2011) – and practitioners (e.g., Cork, 2016) advocate for innovation by rural entrepreneurs, fostering business development, horizontal and vertical integration, networking and cooperation. However, these efforts are not always rewarded: nearly 50% of new products fail (Battor and Battor, 2010), so companies should seek to reduce the risks associated with innovation.

Understanding the drivers behind investment decisions to offer new products, developing new processes, introducing new technologies, or designing new marketing strategies, is a frequent topic in the literature. However, for small firms in rural areas, authors tend to focus only on specific issues (for instance, the adoption of information technologies in farm-based firms). Only few articles analyse the determinants to innovate in the various aspects of firm management by small and medium enterprises (SMEs) in rural areas, in sectors as diverse as manufacturing, retail or services. We identify this as a frequently overlooked area in the literature. Thus, authors such as Quinn et al. (2013) have suggested that future research could explore how the urban versus rural context impacts upon the capacity and nature of innovation. For instance, venture capital investment is most abundant in highly developed regions, particularly urban areas (Heimonen, 2012). In the first part of our article, we provide an ample review of the literature to confirm that this topic is not sufficiently studied.

Then, following the above, we seek to contribute with our choices in both the regional and sectoral instances. Thus, on the one hand, business activities in areas where socioeconomic indicators are weak might be oriented to a 'productive economy' approach, with the logic of using resources from the local economy to sell goods and services outside the rural territory (Bureau, 2016). We choose two quite different sectors to compare, that may easily operate under this approach: firms in agri-food industries and knowledge intensive business services (KIBS). For agri-food firms in particular, authors such as Meynard et al. (2017) have identified numerous signs that highlight the necessity for innovation there, while KIBS are a recurrent example in search of a sectoral diversification of productive activities that rural development policies target. On the other hand, since we are using the Spanish *Technological Innovation Panel* (PITEC) database, which provides annual survey information on the characteristics and innovative activities of a large set of firms, we delimit the rural areas of study to specific NUTS 3 regions in Spain where socioeconomic indicators are weak. The provinces in the North-West area of the Iberian Peninsula are a paradigmatic case in Europe in terms of aging and depopulation. All of them classified as rural or intermediate according to DEGURBA standards, they exhibit a fertility rate and negative vegetative balance among the worst in Europe, driven by a systematic lag in terms of GDP growth compared to the more vigorous Mediterranean provinces.

We use the technology-organisation-environment (TOE) approach as a conceptual framework, in order to identify some recurrent domains in the literature of determinants of innovation. We then develop our analysis in two directions. First, we identify and classify a large list of variables from PITEC database that fit within the different domains in the TOE literature. Second, we use a pooled data set of SMEs from the agri-food industry and knowledge-based services in the rural and intermediate provinces of Asturias, Cantabria, Castilla y León, and Galicia, with the aim of identifying the main drivers of innovation there. Given the limited research available in the field of determinants of innovation by SMEs in rural areas – beyond the classic line of ICT adoption by farms – we conduct an exploratory study to identify the most relevant factors among a large list of indicators. For an exploratory analysis performed to investigate several interconnected causes without hierarchical causality, linear and hierarchical approaches should be avoided (Salvati and Carlucci, 2016). Therefore, we perform a multivariate statistical analysis based on multiple correspondence analysis (MCA) and principal component analysis (PCA) combined, to explore the main drivers of innovation across the two industries among 73 selected indicators from four broad domains, including innovation decisions, organisational, technological and environmental characteristics.

The rest of the article is structured as follows. In the next section, we briefly review the state of arts on the determinants of investment decisions to innovate, with a focus on literature of innovation by SMEs in rural areas in particular. In Section 3, we describe the sample and data of analysis. In the core of our research, Section 4 deals with the multivariate analysis of our data, MCA and PCA, for each of the two industries, and the discussion of the main results obtained. In the final section, we offer a set of conclusions. Complete statistical results and robustness tests are provided in the Supplementary Material (SM).

2. State of arts

2.1 Innovation. Scopes of analysis

The EU Community Innovation Survey (CIS) defines innovation as the introduction of a new or significantly improved product, process, organisational method or marketing method by a firm, implying *newness* in relation to products, processes, or business practices (Johannessen et al., 2001). More than invention alone, innovation can be regarded as an investment appraisal that involves the spotting of opportunities by the firm, considering the risks involved, and taking actions trying to profit out of them (Drucker, 2007).

The determinants of innovation decisions have been analysed in many contexts. Following Fichman (1992), we may distinguish two scopes, whether considering the characteristics of the specific innovation – e.g., the adoption of a specific technology, the investment in research and development (R & D) by the firm, the innovation in products, organisation or marketing methods – or the locus of adoption – that is, the analysis of innovation of specific sectors, by companies alone or in cooperation with others. In fact, the industry sector is one of the factors that have a considerable impact on innovation performance (Zouaghi and Sánchez, 2016), and some authors suggest the interest of conducting research for specific industries in order to better understand innovation (e.g., Ettlie and Rosenthal, 2011).

An extensively studied area explores the determinants of adopting information and communication technologies (ICT), whether oriented to improving productive or organisational processes, or to upgrading customer relationship management (CRM). The methodologies and scopes of analysis are diverse. Ramayah et al. (2016) use structural equation model (SEM) to identify the factors influencing SMEs to continue with their website as a business innovation. Maduku et al. (2016) use the same methodology to identify the key drivers of mobile marketing adoption. Fu and Chang (2015) analyse the factors behind the adoption of cloud consumer relationship management, following TOE theoretical framework, using a fuzzy analytical hierarchy process (FAHP) to estimate the weights of factors in a three-level hierarchical table. Kasanagottu and Bhattacharya (2017) use exploratory factor analysis and multivariate regression to identify IT adoption factors by SMEs in the auto ancillary industry, while Leon-Sigg et al. (2017) offer a qualitative study on IT adoption by SMEs.

Regarding KIBS, Bocquet et al. (2016) highlight the limited research attention on innovation by the KIBS themselves – not as mere intermediaries that provide knowledge for firms' innovation.

Thus, knowledge management by services companies is recently explored by authors like Rodriguez et al (2017), who use logit regression to explore variety in knowledge sourcing and its impact on the degree of novelty in KIBS innovation. Obeidat et al. (2017) use SEM to trace the impact of intellectual capital on knowledge management, and of this on innovation, in telecommunication companies. Zieba and Zieba (2014) find evidence of companies with stronger leadership and employing motivational practices, introducing more new products or processes than their competitors. A related branch of the literature is the analysis of determinants to invest in R & D. R & D is one of the key drivers of innovation (Bascavusoglu-Moreau and Tether, 2012), but its analysis is more frequent in sectors such as manufacturing (e.g., Cohen, 2010) than in others such as energy (e.g., Costa-Campi et al., 2014). The main barriers to invest in R & D identified by the literature on economics of innovation are cost (financial constraints), knowledge (e.g., lack of qualified personnel) and market factors (e.g., a market dominated by established enterprises) (Blanchard et al., 2013).

Other methodologies used to analyse the factors behind innovation and value added are in order. Ellinger et al. (2011) study how supply chain management (SCM) create shareholder value, using Delphi-style opinion data to assess SCM competency, and Altman's (1968) Z-score statistic to measure financial success. Loch and Bode-Greuel (2002) use decision trees to evaluate growth options as sources of financial value for pharmaceutical R & D projects. Wang and Ahmed (2004) test organisational innovation through factor analysis. Moreover, to explore the factors that affect information adoption by agricultural producers, Taragola and van Lierde (2010) use principal component analysis (PCA), and Ali (2012) uses Poison count regression.

2.2 Literature of innovation by SMEs in rural areas

The importance of innovation and knowledge exchange for rural development is clear to some authors (e.g., Rickson, 2016), but the analysis is often limited to specific scopes. A classic one is the analysis of factors behind ICT adoption by farm-based companies (Sonawane, 2014). Early research includes Lewis (1998), who finds that the level of sophistication of adopted farm management information systems (FMIS) is more related to common business factors than to factors distinctive of farming activities, and Gloy and Akridge (2000), who analyse computer and internet adoption on large U.S. farms. Innovations have become important instruments for firms in sectors such as the agri-food industry (Zouaghi and Sanchez, 2016), where firms are mainly product- and process-innovation oriented (Batterink et al., 2006).

Beyond that stream of literature, reviewed in more detail in Section 2.3., only a few articles analyse how companies based in rural areas, in sectors as diverse as manufacturing, industrial, or retail, make investment decisions for innovative practices on products, organisation, distribution, or marketing methods. Although there is extensive research on ICT adoption by firms in emerging countries (e.g., Tob-Ogu et al., 2018; Sanni, 2018), little can be found for rural areas of developed countries. Quinn et al. (2013), for instance, identify a gap in the literature when it comes to analysing the impact on innovation of the urban versus rural context within the small-scale retail industry. The field seems promising, as Blanchard (2017) finds recent evidence of SMEs having a higher level of entrepreneurial ability the more remote their setting and location is, suggesting that remote rural businesses have "a higher developed form of innovative ability that gives them an innate sense of survival" (p. 301).

Some examples of recent literature on innovation by rural firms are in order. Avermaete et al. (2003) highlight the relevance of innovation for small food businesses, and identify age and business size as key determinants. Following Wolfe and Gertler (2002), who assert that innovation is a social enterprise that depends on the capacity of actors within and across firms to learn, Hinrichs et al. (2004) examine the role of social learning in vendor innovation at retail farmers' markets. They find that business innovation there is modest, but social learning through engagement with customers and fellow vendors contributes to innovative marketing and market diversification. Guzman et al. (2008) discuss methodologies and strategies for developing and operating rural living labs for user-driven ICT-based innovative collaborative working environments. Wang (2013) analyse banks' innovation in providing financial services to rural communities in China. Díaz-Pichardo et al. (2017) analyse business innovation processes at the Mexican base of the pyramid, offering evidence of structural differences between urban and rural environments.

2.3 Determinants of investment decisions to innovate

Most research on entrepreneurship and innovation emphasize the individual characteristics and capacities of entrepreneurs, as well as the effect of regional structures (Thornton, 1999). Under a resource-based view (RBV) of the firm (Barney, 1991), which alleges that firm value stems from the combination of resources that are difficult to imitate or imperfectly mobile across firms (Ruivo et al., 2016), a frequent conceptual framework for innovation decisions is the technology-organisation-environment (TOE). Maduku et al. (2016) provide a summary of relevant studies using the TOE applied to a wide range of technologies at firm level, including cloud computing adoption (Alshamaila et al., 2013), electronic supply chain management systems (Lin, 2014), service-oriented architecture (MacLennan and Van Belle, 2014), enterprise resource planning (Ruivo et al., 2014), and green innovation (Weng and Lin, 2011). According to the TOE, the factors that determine innovation are both internal, including the characteristics of the CEOs and the company, and external, considering the characteristics of technological innovation and the environment (Ramayah, 2016). The factors depend on the sector of analysis and the innovative decision, but some recurrent domains are identifiable. The purpose of this section is to list those domains, so in Section 3 we will select, from the set of variables available in the PITEC database, those that fit our list here.

In terms of internal factors, authors test the influence of managers' profiles and traits, as well as the business characteristics. Here, the literature on factors affecting the adoption of ICT by farm-based enterprises is extensive. These would include the sociodemographic profiles of farmers (age, education, income) and attitudes (perceived benefits, support and readiness), farm characteristics (size, type of crops) and business orientation (e.g., the source of management information) (e.g., Alvarez and Nuthall, 2006; Agwu et al.,2008; Tiffin and Balcombe, 2011; Ali, 2012; Adamkolo et al., 2016). In other sectors, the literature on technology investment in the innovation process identifies similar factors. For instance, Venkatesh et al. (2012) also include performance expectations, social influence and facilitating conditions, price value and (IT usage) habit. Idota et al. (2014) include management strategy, management creativity and firms' size (employees and capital base). Finally, regarding small firms, Nieto et al. (2015) find that family firms are more likely to achieve incremental innovations than radical innovations, in line with the traditional view that these firms are more conservative, resistant to change, and averse to risk.

Regarding external factors, we distinguish technological and environmental characteristics. First, the characteristics of an innovation play a fundamental role in its adoption, depending on the expected benefits of such innovation in terms of improved internal processes and productivity (Maduku et al., 2016). Technological characteristics listed in the professional literature include perceived usefulness, relative advantage, cost, security, compatibility and complexity (Ramayah et al., 2016). In terms of environmental factors, one of the most analysed is the degree of competition, with two opposing interpretations (Rodriguez et al., 2017): a negative relationship between innovation and competition by the Schumpeterian view (Schumpeter, 1934), and the Arrovian view, which suggests that competition fosters innovation (Arrow, 1962). In addition, according to the RBV theory, firms require partners' resources to innovate. Two categories are value chain partners (customers and suppliers) and institutional partners (e.g., universities).

3. Sample and data

The analysis is based on data from the Technological Innovation Panel (PITEC), which provides information on innovation activities by a large list of Spanish firms, from years 2010 to 2014.[1] By making use of a pooled data set for a series of years we avoid the statistical inconvenience of having only a few subjects in the sectors and rural areas of analysis.

[1] Five years is fair enough for a statistical analysis with pooled data, while a larger period might be susceptible a structural changes in the decisions to innovate by firms (e.g., before and after the financial crisis). Nonetheless, if we wanted to enlarge the sample, we were limited by the data provided in the PITEC database – in particular, a large set of variables on organisation and marketing innovation, and the objectives of innovation, among others, were included only after 2008.

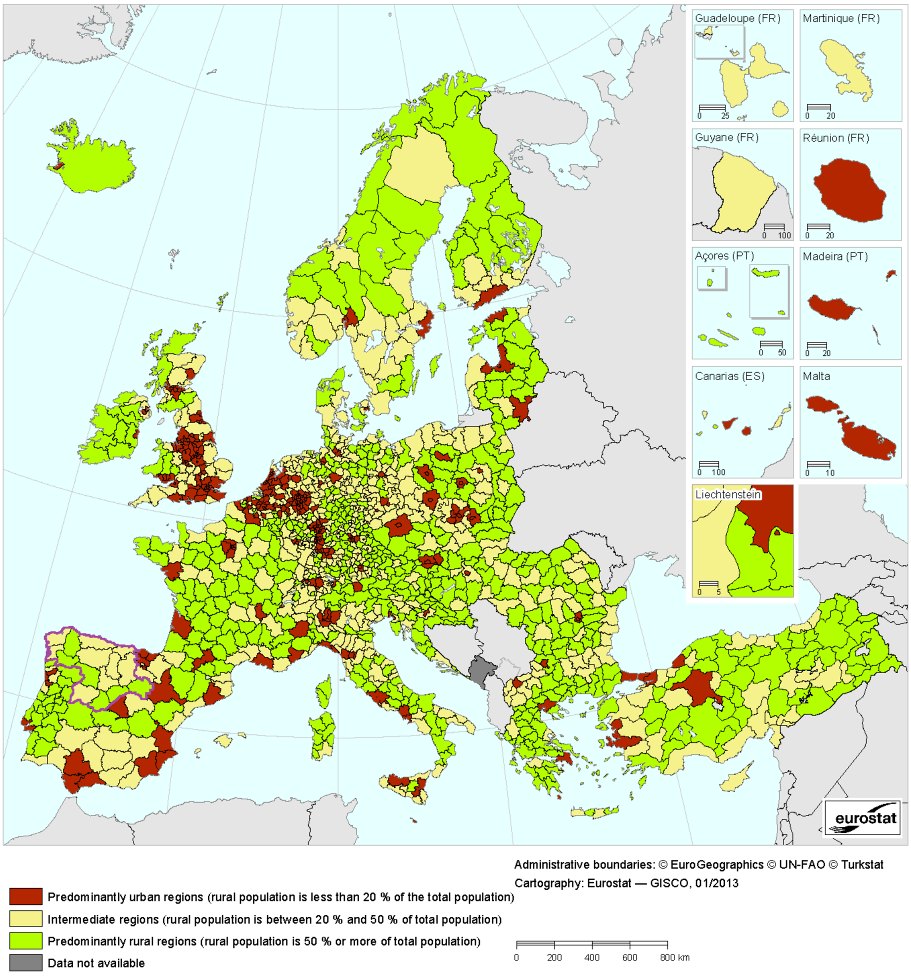
3.1. Sample

We focus on NUTS 3 regions in the North West of the Iberian Peninsula classified as rural or intermediate areas according to Eurostat's DEGURBA methodology:[2] a total of 15 provinces in the Spanish Autonomous Regions of Galicia (4), Asturias (1), Cantabria (1) and Castilla y León (CyL) (9) – see shadowed area in Figure 1. Representing more than one-fourth the size of Spain but less than 15% of its population (140,000 km^2 and 6.75 million inhabitants by year 2017), the area represents a paradigmatic case in Europe of demographic decline: with a density of 48.3 vs. 98.2 inhab/km^2 (mostly driven by CyL well below average), it lost 1.7% of the population in the last two decades while Spain increased 7 million inhabitants (+17.4%). This performance is driven by both natural population performance and the inability of the local economies to attract immigrants. In terms of natural performance, the average age of the population is four years higher than Spain (46.9 vs 43.0), and fertility rate is among the lowest in Europe, ranging in year 2016 from 1.04 children per woman in Asturias to 1.18 in CyL (compared to 1.34 in Spain that year, and 1.58 in EU-28 in year 2015). In terms of economic performance, the GDP per capita was 90% the Spanish average (25,000 euros Spain vs. 22,800 euros), and the annual GDP growth in nominal terms since year 2000 was almost 1.0% lower for all regions but Galicia.[3]

[2] DEGURBA (http://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_DEGURBA)

[3] All sources of data, Instituto Nacional de Estadística (INE), www.ine.es, except fertility rate in Europe (source: Eurostat).

Figure 1. Urban-rural typology for NUTS level 3 regions



Source: Eurostat

Starting with the list of companies in the PITEC database classified as 'with no incidents' (i.e., excluding merged, absorbed, closed and other non-existing firms), we filter the cases of study as companies with personnel in R & D activities in the Autonomous Regions of analysis. In addition, we filter out companies that belong to a corporate group, as well as companies with zero or negative revenues.[4] Then, in terms of sectoral analysis, and following Cork (2016), we are interested in two areas: agri-food sectors, and sectors oriented to technology innovation, such as technological KIBS (t-KIBS), including activities of ICT-related services and R & D consulting (Rodríguez et al., 2017). PITEC replaces the International Standard Industrial Classification (ISIC) codes with 44 aggregated sectors. Thus, regarding t-KIBS companies, we use the following industrial classifications:

[4] Revenues are one of the anonymised variables we use from the PITEC database, together with total investment in physical goods, total investment in innovation, the number of employees in the firm, and in R&D activities in particular. According to the INE, the use of this data for statistical purposes is correct for most statistical and econometric research, since the techniques employed for anonymisation – basically, ranking and grouping observations to estimate their averages – leads to "small biases in any case" (source: PITEC methodological note by the INE, available at http://www.ine.es/prodyser/microdatos/metodologia_pitec.pdf; last access: September 2018). Moreover, since the statistical treatment we perform consists of transforming any numerical (anonymised) variables into quartiles, any biases are avoided.

- Telecommunications, division 61 of ISIC Rev. 4
- Computer programming, consultancy and related activities, division 62 of ISIC Rev. 4
- Software publishing, video and TV, broadcasting, and information services activities, divisions 58, 59, 60 and 63.
- Scientific research and development, division 72.

For agri-food industries, we define them as including (Zouaghi and Sánchez, 2016):

- Agriculture, cattle, forestry, and fishing (divisions 1, 2 and 3 of ISIC Rev. 4).
- Food, beverages, and tobacco (divisions 10, 11 and 12).

Table 1 provides the number of observations by region and sectors considered.

Table 1. Regional and sectoral distribution of observations in the sample

	REGION				
SECTOR	Asturias	Cantabria	CyL	Galicia	Total
KIBS	72	4	134	139	350
	100	44.44	61.19	72.77	71.14
Agri-food	0	5	85	52	142
	0	55.56	38.81	27.23	28.86
Total	72	9	219	191	491
	100	100	100	100	100

Source: Own elaboration.

3.2. Variables

We select variables in PITEC database in two instances: the decisions to innovate by the firms, and the determinants of innovation.

Innovation variables. It includes information about the four types of innovation decisions defined by the CIS, including products, processes, organisational and marketing methods. Thus, we know whether any given company declares to take innovative actions in four areas:

- Innovation on products (innprod) includes either innovation in goods or services.
- Innovation on processes (innproc) considers innovation in production methods, in logistics, and in support to processes.
- Innovation on organisation (inorgn), whether on management systems, work organisation or external relationships.
- Marketing innovation (incomn), whether on product design, distribution channels, market targeting or price strategy.

Following the TOE literature reviewed in Section 2, the determinants of innovation are grouped in three broad domains:

Organisation. It includes internal variables referring either to the managers or to the firm itself.

- Managers: we consider measures of manager support, or propensity to act, and the perceived benefits (performance expectations).
- Firm: we include measures of firm size, prior technology use, whether financial resources are available, and IT capabilities of employees. Business type, another classic in the literature, is already acknowledged by including agri-food and t-KIBS firms in particular.

Technology. It includes external factors referred to the characteristics of the intended innovation. We consider variables in the PITEC database of three types:

- Relative advantage: it considers the perceived usefulness in terms of the expected improvement of products, internal processes, productivity, and marketing success.
- Complexity: the difficulty of developing or adopting such technology, including the type of research required.
- Cost: the level of resources required to develop the innovation.

Environmental. Including external factors as well, we consider variables in three domains:

- Competitive pressure: to trace evidence of either a positive or a negative relationship between innovation and degree of competition.
- Value chain: it includes the customer pressure to improve goods and services, as well as any facilitating conditions by suppliers.
- Social influence: including institutional partners and any other sources of information to innovate.

The list of variables selected from the PITEC database that fit the domains above, their description, and the main descriptive statistics are provided in Table 2.

Table 2. Variables and descriptive statistics

VARIABLE	DEFINITION	type	recoded	MCA		Descriptive statistics				
						N	Mean	Std. Dev	Min	Max
INNOVATION										
Innovation in product / services										
innprod	Innovation in products	dummy 0 - 1		1	INNOPROD	491	0.68	0.47	0.0	1.0
innobien	Innovation in goods	dummy 0 - 1		1	INNOPROD	491	0.46	0.50	0.0	1.0
innoserv	Innovation in services	dummy 0 - 1		1	INNOPROD	491	0.48	0.50	0.0	1.0
Innovation in processes										
innproc	Innovation in processes	dummy 0 - 1		2	INNOPROC	491	0.57	0.50	0.0	1.0
innfabri	Innovation in productive methods	dummy 0 - 1		2	INNOPROC	491	0.38	0.49	0.0	1.0
innlogis	Innovation in logistics	dummy 0 - 1		2	INNOPROC	491	0.14	0.35	0.0	1.0
innapoyo	Innovation in support to processes	dummy 0 - 1		2	INNOPROC	491	0.37	0.48	0.0	1.0
Innovation in organization										
inorgn1	Innov. organization: management systems	dummy 0 - 1		3	INNORG	491	0.46	0.50	0.0	1.0
inorgn2	Innov. organization: work	dummy 0 - 1		3	INNORG	491	0.46	0.50	0.0	1.0
inorgn3	Innov. organization: external relationships	dummy 0 - 1		3	INNORG	491	0.28	0.45	0.0	1.0
Innovation in marketing										
incomn1	Innov. marketing: product design	dummy 0 - 1		4	INNOMARKT	491	0.26	0.44	0.0	1.0
incomn2	Innov. marketing: distribution channels	dummy 0 - 1		4	INNOMARKT	491	0.26	0.44	0.0	1.0
incomn3	Innov. marketing: market targeting	dummy 0 - 1		4	INNOMARKT	491	0.24	0.43	0.0	1.0
incomn4	Innov. marketing: price strategy	dummy 0 - 1		4	INNOMARKT	491	0.15	0.36	0.0	1.0
ORGANISATION (internal):										
Managers										
CEO support / expectations										
tipoid	R & D: recoded as '1 = occasional; 2 = frequent'	categ. 1 ← 2	recoded 1 → 2	5	CEO	491	1.87	0.33	1.0	2.0
innexpense	Ratio of total innovation expenses to revenues	numerical	ranked by quartiles	5	CEO	490	2.50	1.12	1.0	4.0
rdempl	Ratio of employees in R & D to employees	numerical	ranked by quartiles	5	CEO	490	2.50	1.12	1.0	4.0
Firm										
fim size (employees / capital base)										
revenues	Sales revenues	numerical	ranked by quartiles	6	SIZE	490	2.50	1.12	1.0	4.0
employees	Number of employees	numerical	ranked by quartiles	6	SIZE	482	2.51	1.13	1.0	4.0
age	Log (# years since the company was launched)	numerical	ranked by quartiles	6	SIZE	490	2.50	1.12	1.0	4.0
prior technology use / IT usage habit										
fuente1	Information source: within the firm	categ. 1 ← 4	recoded 1 → 4	7	IT USE	491	3.51	0.71	1.0	4.0
pat	Patent applicaton	dummy 0 - 1		7	IT USE	491	0.16	0.37	0.0	1.0
availability of financial resources										
face1	Relevant factors: No internal financing	categ. 1 ← 4	recoded 1 → 4	8	RESOURCES	491	3.32	0.84	1.0	4.0
face2	Relevant factors: No external financing	categ. 1 ← 4	recoded 1 → 4	8	RESOURCES	491	3.33	0.86	1.0	4.0
inver	Gross investment in physical goods	numerical	ranked by quartiles	8	RESOURCES	390	2.89	0.92	1.0	4.0
employee IT capability										
faci1	Relevant factors: No qualified personnel	categ. 1 ← 4		9	EMPLOYEE	491	2.76	0.79	1.0	4.0
remusup	Perc. of employees with higher education	numerical	ranked by quartiles	9	EMPLOYEE	461	2.59	1.09	1.0	4.0
mujeres	Percentage of women	numerical	ranked by quartiles	9	EMPLOYEE	476	2.51	1.07	1.0	4.0
TECHNOLOGY (external):										
relative advantage										
objet1	Objective: Wider range of goods / services	categ. 1 ← 4	recoded 1 → 4	10	GROWTH	491	3.25	0.95	1.0	4.0
objet2	Objective: Substitute products / processes	categ. 1 ← 4	recoded 1 → 4	10	GROWTH	491	2.68	1.08	1.0	4.0
objet4	Objective: Higher market share	categ. 1 ← 4	recoded 1 → 4	10	GROWTH	491	3.05	0.99	1.0	4.0
gradcom1	Innomarkt - Objective: Higher market share	categ. 1 ← 4	recoded 1 → 4	10	GROWTH	188	3.32	0.73	1.0	4.0
objet3	Objective: New markets	categ. 1 ← 4	recoded 1 → 4	11	NEW MARKETS	491	3.12	1.01	1.0	4.0
gradcom2	Innomarkt - Objective: New customer segments	categ. 1 ← 4	recoded 1 → 4	11	NEW MARKETS	188	3.19	0.81	1.0	4.0
gradcom3	Innomarkt - Objective: New markets	categ. 1 ← 4	recoded 1 → 4	11	NEW MARKETS	188	3.05	0.86	1.0	4.0
objet5	Objective: Greater quality of goods / services	categ. 1 ← 4	recoded 1 → 4	12	QUALITY	491	3.32	0.89	1.0	4.0
objet6	Objective: More flexibility in production / services	categ. 1 ← 4	recoded 1 → 4	12	QUALITY	491	2.86	1.05	1.0	4.0
objet7	Objective: Greater capacity in production / services	categ. 1 ← 4	recoded 1 → 4	12	QUALITY	491	2.94	1.02	1.0	4.0
gradorg3	Innorg - Objective: Greater quality of goods / servs	categ. 1 ← 4	recoded 1 → 4	12	QUALITY	244	3.48	0.66	1.0	4.0
objet8	Objective: Lower labor costs per unit produced	categ. 1 ← 4	recoded 1 → 4	13	COST	491	2.44	1.03	1.0	4.0
objet9	Objective: Fewer materials per unit produced	categ. 1 ← 4	recoded 1 → 4	13	COST	491	2.05	1.00	1.0	4.0
objet10	Objective: Less energy per unit produced	categ. 1 ← 4	recoded 1 → 4	13	COST	491	2.20	1.09	1.0	4.0
gradorg4	Objective: Lower unit costs	categ. 1 ← 4	recoded 1 → 4	13	COST	244	2.80	0.97	1.0	4.0

VARIABLE	DEFINITION	type	recoded	MCA		N	Mean	Std. Dev	Min	Max
objet11	Objective: Reduced environmental impact	categ. 1 ← 4	recoded 1 → 4	14	RULES	491	2.26	1.15	1.0	4.0
objet12	Objective: Better health / security	categ. 1 ← 4	recoded 1 → 4	14	RULES	491	2.23	1.14	1.0	4.0
objet13	Objective: Regulatory compliance	categ. 1 ← 4	recoded 1 → 4	14	RULES	491	2.38	1.21	1.0	4.0
objet14	Objective: Increasing total employment	categ. 1 ← 4	recoded 1 → 4	15	EMPLOYMENT	491	2.34	1.00	1.0	4.0
objet15	Objective: Increasing qualified employment	categ. 1 ← 4	recoded 1 → 4	15	EMPLOYMENT	491	2.50	1.09	1.0	4.0
objet16	Objective: Maintaning employment	categ. 1 ← 4	recoded 1 → 4	15	EMPLOYMENT	491	2.88	1.10	1.0	4.0
gradorg1	Innorg - objective: Reduced time of response	categ. 1 ← 4	recoded 1 → 4	16	TIME INFO	244	3.20	0.84	1.0	4.0
gradorg2	Innorg - objective: Ability to develop new products	categ. 1 ← 4	recoded 1 → 4	16	TIME INFO	244	3.29	0.80	1.0	4.0
gradorg5	Innorg - objective: Better information exchange	categ. 1 ← 4	recoded 1 → 4	16	TIME INFO	244	3.18	0.79	1.0	4.0
complexity										
faci2	Relevant factors: No information about technology	categ. 1 ← 4	recoded 1 → 4	17	COMPLEX	491	2.13	0.75	1.0	4.0
faci3	Relevant factors: No information about markets	categ. 1 ← 4	recoded 1 → 4	17	COMPLEX	491	2.26	0.81	1.0	4.0
infun	Fundamental research	numerical	recoded as dummy	18	RESEARCH	491	0.15	0.35	0.0	1.0
inapl	Applied research	numerical	recoded as dummy	18	RESEARCH	491	0.66	0.47	0.0	1.0
destec	Technological development	numerical	recoded as dummy	18	RESEARCH	491	0.71	0.45	0.0	1.0
cost										
face3	Relevant factors: High innovation costs	categ. 1 ← 4	recoded 1 → 4	8	RESOURCES	491	3.04	0.98	1.0	4.0
ENVIRONMENTAL (external):										
competitive pressure										
otrofac1	Relevant factors: Market dominated by competitors	categ. 1 ← 4	recoded 1 → 4	19	COMPETITORS	491	2.66	0.94	1.0	4.0
fuente4	Information source: competitors	categ. 1 ← 4	recoded 1 → 4	19	COMPETITORS	491	2.44	0.97	1.0	4.0
value chain: vendor support / customer pressure										
fuente2	Information source: suppliers	categ. 1 ← 4	recoded 1 → 4	20	VALUE CHAIN	491	2.64	1.00	1.0	4.0
fuente3	Information source: customers	categ. 1 ← 4	recoded 1 → 4	20	VALUE CHAIN	491	2.96	1.01	1.0	4.0
otrofac2	Relevant factors: Uncertain demand	categ. 1 ← 4		20	VALUE CHAIN	491	2.17	0.95	1.0	4.0
otrofac4	Relevant factors: No demand for innovative goods	categ. 1 ← 4		20	VALUE CHAIN	491	3.52	0.75	1.0	4.0
social influence										
parque	Located in a science or technology campus	dummy 0 - 1		21	SOCIAL	491	0.21	0.41	0.0	1.0
faci4	Relevant factors: No partners for innov. cooperation	categ. 1 ← 4		21	SOCIAL	491	2.48	0.98	1.0	4.0
fuente5	Information source: consulting	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.24	0.99	1.0	4.0
fuente6	Information source: universities	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.53	1.10	1.0	4.0
fuente7	Information source: public agencies	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.15	1.08	1.0	4.0
fuente8	Information source: technology centers	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.31	1.13	1.0	4.0
fuente9	Information source: conferences	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.58	0.97	1.0	4.0
fuente10	Information source: academic journals	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.54	0.99	1.0	4.0
fuente11	Information source: professional associations	categ. 1 ← 4	recoded 1 → 4	21	SOCIAL	491	2.20	0.94	1.0	4.0

All categorical variables coded in PITEC database as 1=high; 2=intermediate; 3=low; 4=not relevant were recoded inversely except where noted

Source: Own elaboration.

4. Multivariate statistical analysis. Results

Multivariate statistical techniques are useful to explore a large number of variables, particularly suitable for the analysis of complex processes without hierarchical causality. Among the techniques available to reduce the number of variables of study we find MCA, PCA and other factorial analyses, optimal scaling, and others. PCA is often used to explore a phenomenon to identify latent variables, while econometric approaches such as SEM are used to confirm a research investigation by testing a priori hypotheses (e.g., Yeh et al., 2010).

PCA helps by reducing the dimensionality of the data, requiring only to interpreting a few components. However, it assumes linear relationships between numeric variables, when most variables in our dataset are categorical. Alternatives to solve this problem include non-linear or categorical PCA (NLPCA/CATPCA), which converts every category into a numerical value using optimal quantification (Linting et al., 2007).

Our alternative follows a two-step approach, by performing a combination of MCA and PCA. First, we start from the categorical variables in each domain to make indices for the different domains making use of MCA. Articles that follow a similar approach include Asselin and Anh (2008), and Ezzrari and Verme (2012). Then, we conduct a standard PCA by making use of the indices, to analyse and interpret the domains ultimately associated with the different innovation decisions for companies in both sectors. In brief, using plain words, MCA help us to summarize the data available within each domain, while it transforms information that is often expressed in qualitative terms – such as "the company finds the relevance of this feature for innovation purposes to be high/medium/low" – into numerical data. Then, PCA is used to identify which domains appear to be determinant in the different innovation activities by the firms.[5]

4.1. Multiple Correspondence Analysis

MCA is a multivariate statistical technique oriented to analyse categorical data. It allows to explore the interdependence between categorical variables that are at the same level (i.e., none of them are considered to be dependent or causal), by reducing the dimensionality of the data based on the chi-square distance rather than linear correlations or Euclidean distances (Greenacre, 2016)

Table 2 provides the list of domains where MCA was applied, separately to each of them. In most cases, they correspond with the list of domains identified in the literature, described in Section 3. Nonetheless, some exceptions follow. First, the relative advantage of the technology, which makes use of a large set of indicators in the survey about the objective of innovation by the firm, is split into seven domains, whether the objective is related to growth, reaching new markets, enhanced quality of products or services, reducing costs, regulatory compliance, fostering employment, or better using information and reducing time response. Second, the complexity of developing or adopting a technology is split in two domains, whether they refer to the complexity to adopt it or the type of research to be developed. Third, we trace only one variable to be considered as a proxy for the cost of innovation. Since MCA requires at least two variables to be implemented, we opt to include it in group 8 – financial restrictions.

MCA is performed in three steps. First of all, the numerical variables were transformed into quartiles, with the exception of the three variables in the domain 'research', now recoded as binary dummies – whether firms implement that sort of R & D or not. Then, to maintain coherence within

[5] Any statistical treatment implies loss of information, and this implies some limitations to our research. In particular, the reduction of variables into domains performed by MCA implies an initial loss of information, although inevitable, as there is no univocal relationship between variables. Then, PCA uses MCA results to describe the structure of the relationship between the different domains on which we base our conclusions. However, these are only descriptive observations that do not allow to test theoretical hypotheses. These should first be defined (here, exploratory analysis can be useful) and then tested using confirmatory techniques.

data for the sake of interpretation, since the order of categorical variables coded 1 – 4 in the PITEC database is ascending (ranging from 1='high relevance' to 4='not relevant'), they were recoded inversely. Only five of them were not recoded, for coherence within the domains they were included – see Table 2. For the same reason, variable 'tipoid' was recoded as 1='occasional R&D' and 2='frequent R&D'.

Secondly, we use Goodman and Kruskal's gamma to check whether the variables we assumed to fall within a specific domain are indeed related (ranges may fall within -1 and 1). The complete results are provided in Table A1 in the SM. In brief, most domains include variables that are strongly positively related pairwise (i.e., values close to one), particularly those referred to the innovation domains. The most notable exceptions are the domains 'IT use' and 'Employee', which include variables that appear to be independent. These constructs must be carefully considered when interpreting their results in the subsequent PCA analysis. In addition, two constructs include coherent variables with some exception: the variables 'technological development' (destec) in the 'Research' domain and 'located in a technological campus' (parque) in the 'Social' domain relate inversely to the other variables in their domains, and the absence of partners for innovation cooperation (faci4) seems to be independent with other variables in the 'Social' domain.

Thirdly, MCA is implemented to obtain the indicators to be used in the PCA analysis. In first instance, the whole sample is considered to determine the MCA dimension whose coordinates are to be used as indicator of each domain, as well as to interpret their sign. Missing values are replaced by average data, as standard in the package FactoMineR (Le et al., 2008). The selected dimension would be the one with variables in that specific domain being ranked in a coherent manner, which is usually the one with the highest proportion variance explained. The only exceptions are domains 'employee' and 'research', for which the second domain was selected. In addition, coordinates were inverted for eleven domains for the sake of interpretation of results in the subsequent PCA analysis. The analysis is complemented with a Cronbach's Alpha analysis – see Table A2 in the SM. The results obtained confirm the poor reliability of constructs for domains 'IT use' and 'Employee' identified in the Goodman and Kruskal's gamma analysis, and highlight other three domains with weak reliability ('Time info', 'Competitors', and 'Value chain'). Notwithstanding, the overall results have internal validity if a majority of constructs in the analysis have satisfactory alphas (e.g., McKinley et al., 1997). Finally, the MCA is implemented for each sector separately. Table 3 provides the main descriptive statistics of the dimensions obtained, separately, for firms in the agri-food and t-KIBS sectors. These are the coordinates to be used in the PCA that follows next.

Table 3. MCA results – descriptive statistics

				Descriptive statistics							
Domain	Variance expl.	Sector	MCA Indicator	N	Mean	Std. Dev	Min	p25	Median	p75	Max
1	66.0%	agrifood	1 INNOPROD	142.00	0.00	0.83	-0.98	-0.98	0.53	0.53	1.07
		t-kibs		349.00	0.00	0.82	-1.23	-1.23	0.29	0.84	0.84
1	56.0%	agrifood	2 INNOPROC	142.00	0.00	0.75	-1.21	-0.68	-0.19	0.99	0.99
		t-kibs		349.00	0.00	0.76	-1.48	-0.39	-0.37	0.74	0.74
1	68.0%	agrifood	3 INNORG	142.00	0.00	0.81	-0.67	-0.67	-0.67	0.86	1.55
		t-kibs		349.00	0.00	0.83	-0.89	-0.89	-0.21	0.49	1.15
1	55.0%	agrifood	4 INNOMARKT	142.00	0.00	0.77	-1.96	-0.49	0.55	0.55	0.55
		t-kibs		349.00	0.00	0.75	-0.53	-0.53	-0.53	0.64	1.89
1	27.0%	agrifood	5 CEO	142.00	0.00	0.76	-0.64	-0.59	-0.40	0.42	1.96
		t-kibs		349.00	0.00	0.79	-2.24	-0.48	0.25	0.56	0.87
1	23.4%	agrifood	6 SIZE	142.00	0.00	0.87	-1.67	-0.71	0.36	0.79	0.87
		t-kibs		349.00	0.00	0.82	-1.81	-0.39	0.16	0.60	1.09
1	26.0%	agrifood	7 IT USE	142.00	0.00	0.74	-3.56	-0.17	0.50	0.50	0.50
		t-kibs		349.00	0.00	0.73	-1.43	-0.13	0.27	0.27	2.30
1	18.6%	agrifood	8 RESOURCES	142.00	0.00	0.77	-2.69	-0.04	0.28	0.42	0.58
		t-kibs		349.00	0.00	0.72	-2.21	-0.19	0.18	0.54	0.80
2	12.9%	agrifood	9 EMPLOYEE	142.00	0.00	0.64	-2.22	-0.31	0.06	0.39	1.12
		t-kibs		349.00	0.00	0.63	-2.16	-0.37	-0.14	0.31	1.45
1	19.1%	agrifood	10 GROWTH	142.00	0.00	0.72	-0.53	-0.46	-0.40	0.19	1.89
		t-kibs		349.00	0.00	0.68	-2.77	0.10	0.27	0.36	0.44
1	19.7%	agrifood	11 NEW MARKETS	142.00	0.00	0.62	-0.80	-0.48	-0.04	0.28	2.01
		t-kibs		349.00	0.00	0.59	-0.95	-0.50	-0.32	0.57	0.74
1	20.0%	agrifood	12 QUALITY	142.00	0.00	0.70	-0.80	-0.54	-0.24	0.39	1.83
		t-kibs		349.00	0.00	0.75	-2.68	0.12	0.31	0.41	0.43
1	22.3%	agrifood	13 COST	142.00	0.00	0.81	-0.67	-0.54	-0.44	0.23	1.59
		t-kibs		349.00	0.00	0.76	-1.15	-0.91	0.11	0.72	1.18
1	28.1%	agrifood	14 RULES	142.00	0.00	0.92	-1.72	-0.39	0.42	0.65	0.83
		t-kibs		349.00	0.00	0.92	-1.15	-1.14	0.25	0.80	1.27
1	28.3%	agrifood	15 EMPLOYMENT	142.00	0.00	0.93	-0.78	-0.71	-0.63	0.82	1.46
		t-kibs		349.00	0.00	0.92	-2.08	0.39	0.46	0.51	0.56
1	18.5%	agrifood	16 TIME INFO	142.00	0.00	0.53	-1.14	0.00	0.00	0.00	1.62
		t-kibs		349.00	0.00	0.54	-1.47	-0.18	0.00	0.05	1.09
1	30.6%	agrifood	17 COMPLEX	142.00	0.00	0.99	-0.59	-0.52	-0.44	-0.39	2.19
		t-kibs		349.00	0.00	0.95	-0.51	-0.46	-0.46	-0.43	2.19
2	35.0%	agrifood	18 RESEARCH	142.00	0.00	0.60	-0.27	-0.27	-0.15	-0.15	2.01
		t-kibs		349.00	0.00	0.58	-0.78	-0.06	-0.05	-0.05	1.25
1	20.8%	agrifood	19 COMPETITORS	142.00	0.00	0.83	-1.48	-0.62	0.06	0.57	1.42
		t-kibs		349.00	0.00	0.79	-0.79	-0.65	-0.31	0.15	2.32
1	13.0%	agrifood	20 VALUE CHAIN	142.00	0.00	0.62	-1.79	-0.40	0.19	0.42	0.87
		t-kibs		349.00	0.00	0.66	-0.77	-0.41	-0.13	0.14	2.86
1	15.6%	agrifood	21 SOCIAL	142.00	0.00	0.65	-1.35	-0.49	0.10	0.61	0.92
		t-kibs		349.00	0.00	0.67	-0.86	-0.60	-0.14	0.52	1.66

Source: Own elaboration.

4.2 Principal Component Analysis

Using the coordinates extracted by the MCA for the 21 indicators in the previous section, we perform a PCA analysis. The purpose of PCA is to explain the variance-covariance structure of a set of variables by creating new, uncorrelated variables, from linear combinations of the original ones. It helps to simplify the analysis: only few components are now required which represent much of the original information, allowing to interpreting the relations among the original variables in a way that might not be obvious with direct observation (Johnson and Wichern, 2014).

We perform a PCA, separately, for firms in the agri-food and t-KIBS sectors. We use the Keiser–Meyer–Olkin (KMO) measure of sampling adequacy, which tests whether the partial correlations among variables are small, and Bartlett's test of sphericity, which tests whether the correlation matrix is an identity matrix. We obtain KMO values of 0.651 and 0.734 for the agri-food and t-KIBS sector, respectively, and a p-value less than 0.001 for the Bartlett's test, what confirms the sample is adequate. We considered six significant components, which account for a cumulated variance higher than 60% for the whole sample. Nonetheless, the main justification for the selection of components is the theoretical interpretability of the results – which we discuss below. We then performed a varimax rotation to the components obtained,[6] in order to get each variable associated with higher loads to a single component. For robustness, results for 4 to 8 components, as well as for none rotation, promax, cluster and quartimax rotations for 6 components, were also obtained – complete results available in Tables A3 and A4 in the SM.

Results of the PCA carried out on the matrix composed by the 21 domains, separately for the sectors of analysis, are summarized in Table 4, with loadings smaller than |0.2| omitted for clarity. Loadings – the coefficients of each indicator in the linear function of a given component – measure the importance of such variable in the component. Communality (h2) in factorial analysis represents the part of the variance of a variable that contributes to the formation of the components, and uniqueness (u2) the part that represents its specific behaviour.

[6] For such purpose, we use the package *psych* of the R statistical suite (Revelle, 2017).

Table 4. Principal component analysis (PCA) factor loadings

Agrifood

	RC1	RC2	RC3	RC4	RC5	RC6	h2	u2
INNOPROD	-0.23			**0.76**			0.67	0.33
INNOPROC				**-0.73**	0.29		0.69	0.31
INNORG		-0.30		0.58		-0.44	0.63	0.37
INNOMARKT				-0.41		**0.68**	0.65	0.35
CEO		**0.87**					0.78	0.22
SIZE		**-0.85**		0.28			0.82	0.18
IT USE						**0.66**	0.48	0.52
RESOURCES	-0.25		-0.27		**-0.75**		0.72	0.28
EMPLOYEE		**0.69**	0.28				0.64	0.36
GROWTH	0.54		**0.64**			-0.21	0.75	0.25
NEWMARKETS			**0.72**				0.58	0.42
QUALITY	**0.85**						0.77	0.23
COST	**0.82**			-0.25			0.75	0.25
RULES	**-0.77**						0.67	0.33
EMPLOYMENT	**0.85**						0.75	0.25
TIME INFO			**0.60**	-0.30			0.52	0.48
COMPLEX					**0.81**	0.24	0.76	0.24
RESEARCH				0.22	-0.43		0.27	0.73
COMPETITORS			**0.72**		0.26		0.59	0.41
VALUE CHAIN		0.34			0.37	-0.28	0.35	0.65
SOCIAL	-0.50					-0.45	0.55	0.45
	RC1	**RC2**	**RC3**	**RC4**	**RC5**	**RC6**		
SS loadings	3.528	2.312	2.049	2.031	1.847	1.613		
Proportion Var	0.168	0.110	0.098	0.097	0.088	0.077		
Cumulative Var	0.168	0.278	0.376	0.473	0.561	0.638		

t-KIBS

	RC1	RC2	RC3	RC6	RC4	RC5	h2	u2
INNOPROD		0.51				0.52	0.57	0.43
INNOPROC	-0.22	**-0.67**					0.55	0.45
INNORG		**0.72**					0.59	0.41
INNOMARKT		**0.81**					0.70	0.30
CEO			**0.74**			0.23	0.66	0.34
SIZE		-0.36		0.28	**0.63**		0.64	0.36
IT USE			-0.50		0.54		0.58	0.42
RESOURCES					0.47		0.26	0.74
EMPLOYEE			0.25	**0.81**			0.73	0.27
GROWTH	**0.61**			-0.33		0.28	0.60	0.40
NEWMARKETS					0.23	0.57	0.44	0.56
QUALITY	**0.75**	0.22					0.66	0.34
COST	**-0.64**	-0.22	-0.36		-0.21	0.23	0.68	0.32
RULES	0.41	0.21	0.53			-0.40	0.71	0.29
EMPLOYMENT	**0.69**						0.50	0.50
TIME INFO	0.30	-0.31	-0.29		-0.47		0.53	0.47
COMPLEX				**0.73**			0.63	0.37
RESEARCH	0.23		0.53				0.35	0.65
COMPETITORS	-0.32	0.22	-0.25	0.35		-0.49	0.58	0.42
VALUE CHAIN	-0.53	0.21		0.48		-0.30	0.69	0.31
SOCIAL	-0.26		-0.58	0.42	0.22		0.63	0.37
	RC1	**RC2**	**RC3**	**RC6**	**RC4**	**RC5**		
SS loadings	2.778	2.404	2.130	2.047	1.499	1.415		
Proportion Var	0.132	0.114	0.101	0.097	0.071	0.067		
Cumulative Var	0.132	0.246	0.347	0.444	0.515	0.582		

Notes: The order of the rotated components (RC) changed after the rotation for t-KIBS. Loadings < |0.2| were omitted for clarity. Proportion Var indicates the variance extracted by each component and u2 the uniqueness of each variable. Variables with a high uniqueness (u2 > 0.5) were marked with the colour off. Bold data (loadings > |0.6|) are highlighted to identify the relevant domains associated with each component.

Source: Own elaboration.

4.3. Results

Since we deal with four broad domains (the decisions to innovate on one hand, and the organisational, technological and environmental determinants on the other), and innovation may take as well the form of four alternative decisions, a minimum of four components were considered. Eventually, six components were extracted for both sectors, considering the variance extracted by each component, the total variance extracted, obtaining a sufficiently low uniqueness of the four innovation variables, and using the same number of components in both sectors for the sake of comparability.

The six components account for 63.8% of the total variance for the agri-food sector, and 58.2% for the t-KIBS. Loadings > |0.6| were highlighted to show which domains are associated with each component. In both instances, the first component corresponds to the relative advantage of the innovation (where growth, quality, cost and employment are shared by both sectors). The most interesting component comes in second instance for t-KIBS, and fourth for agri-food: the four innovation decisions are grouped in this category for t-KIBS firms and, with some nuance, for agri-food firms as well. This tells us two things. First, product and organisational innovation tend to come together, and, when firms innovate in such instances, they often do not consider innovation in processes. Marketing innovation decisions seem to be independent for agri-food firms, related to specific factors (see RC6 next), and more related in t-KIBS to organisational innovation.

Second, any relationships between the innovation indicators and other variables with significant loadings within those two components are meaningful. In the agri-food sector, the distinctive behaviour of marketing innovation is noteworthy: the indicator loads on the sixth rotated component as well, with a higher loading, only for companies of that sector. The most relevant related factors are previous ICT use related to marketing innovation (RC6) – undermined by the above-mentioned lack of reliability of our construct *IT use* – , and weaker relations between production and organisational innovation with firm size, among others. For the t-KIBS sector, the uniqueness of the innovation indicators is high and the loadings of other variables in RC2 are quite low. This again suggests a high variability within the services sectors included. Notwithstanding, for robustness of interpretation, we trace results back for 4 components and forth for 8 components, to confirm that the four innovation decisions are related to firm size (all but process innovation are negatively related, meaning that smaller companies seek to innovate more), and that product (services) innovation is positively related to searching for new markets and negatively to competitive pressure.

The other three rotated components, which extract about 28% of total variance altogether, have significant loadings higher than |0.6| for indicators in the following domains. First, firm internal characteristics appear in RC2 for agri-food and RC4 for services companies, but with different items: CEO support and employee ICT capabilities come together in smaller agri-food firms, while firm size, former ICT use and availability of financial resources come together in t-KIBS firms. Second, factors related to the relative advantage of innovation appear in RC3 and RC6, respectively, but again with different profiles: searching for growth and new markets is related to competitive pressure in agri-food firms, while for services companies the factors that come together would be employee capabilities and technology complexity. Third, the last component (RC5 and RC3, respectively), would include a more diverse combination of factors: for agri-food companies, not having resources available and complex technologies are two problems that often come together, while for t-KIBS this domain includes factors related to CEO support (positively to objectives of regulatory compliance, investing in fundamental or applied research, and negatively to social factors).

This way, the results obtained justify, from a theoretical perspective, the number of components and rotation techniques used, both because there is an interpretable correspondence between components and domains, and because these correspondences are somehow stable when agri-food and t-KIBS are compared. Moreover, results are highly robust, in qualitative terms, to alternative rotations.

We may formulate these results in terms of what would be the basic latent variables to be tested in a structural equation model. Nonetheless, this suggestion is only on an early stage for a model development, since the relationship among the observed variables and latent variables may be more complex. Thus, a model of innovation by t-KIBS firms might include the four innovation decisions together (although some specificities for product innovation can be considered), while marketing innovation by agri-food firms might use a specific model. A first latent variable in both models would be the *perceived relative advantage of innovation*, with observed variables being the objectives to increase market share (t-KIBS firms), provide goods of greater quality, reduce unit costs, and increasing employment.

For agri-food firms, the objectives to increase market share, targeting new markets, developing new products and reducing the time of response come together, and seem to be related with the extent of competitive pressure. This suggests a formative latent variable, *market competition*, for firms of this sector. In addition, CEO support, employee ICT capabilities and firm size come together. The three variables are internal organisation characteristics, suggesting a latent variable for a *tendency to innovate*. Lastly, the lack of resources and technology complexity would be the observed variables for *restrictions to innovate*. A model for marketing innovation by agri-food firms should consider previous ICT use as an additional factor for a latent *experience*.

For services firms, technology complexity and employee capabilities come together in a *relevance* latent variable. Firm size, former ICT use and availability of financial resources seem to be here the relevant internal organisation characteristics for *restrictions to innovate*. Finally, CEO support and the objectives of regulatory compliance and investing in fundamental or applied research would be indicative of a *tendency to innovate*. In addition, we might include an additional latent factor to explain product innovation, *market competition*, which would include searching for new markets and competitive pressure as observed variables.

4.4. Results compared to previous studies

In the previous section, the exploratory analysis with MCA and PCA has helped to identify a series of factors that would drive innovation by agri-food and t-KIBS firms in rural areas. Now, the purpose of this section is to compare those findings against previous results in the literature.

Our research highlights the necessity to study innovation by rural SMEs in sectors other than agriculture: a viable rural model requires a sectoral transition that faces the progressive loss of employment in the primary sector (López Iglesias, 2013). However, the analysis of innovation by SMEs in rural areas, other than agriculture, is a frequently overlooked area in the literature. Among the exceptions, we may cite the following. Capitanio et al. (2010) focus on the agri-food industry, and find that the location of the firm in rural areas of Italy positively affected product innovation. Contrariwise, Heimonen (2012) compares innovation by growing SMEs in two diverse regions of Finland, but finds little difference in the level of innovation between rural and urban SMEs. Beyond that debate, we confirm a couple of results by Capitanio et al. (2010), who observe a link of process innovation with financial structure and debt level – satisfied by our rotated component RC5 in Table 4 – and R & D positively affecting the adoption of innovation – weakly observed in RC4.

For other results, instead, we cannot offer confirming results. Thus, Heimonen (2012) finds a positive correlation between innovativeness and the productivity of labour, which may result from an increase in capital intensiveness. We do observe a relationship between employee IT capability and financial constraints for agri-food firms, but no relation to a specific innovative action. Kasabov (2011) analyses how peripheral firms in the biotech sector collaborate through clusters, to find that failed clusters are related to lack of local capacity in basic science and to attract good scientists and good managers. Our analysis shows a relationship between R & D and CEO support for t-KIBS firms, but no link of them two to a specific innovation action. Finally, Joffre et al. (2017) find that the transfer of technology is the predominant approach to innovation in the aquaculture sector. Again, we do observe that complex technologies and lack of resources often come together for agri-food companies, but no link to a specific innovation action. Other articles in the literature suggest the necessity to focus more on constructs such as *social*, *competitors* and *value chain*, for which we do not obtain particularly relevant results (we may be biased due to the above-mentioned low reliability of the constructs for competitors and value chain). Examples are Brunori et al. (2013) and Ingram (2015), who observe the importance of innovation networks of producers, customers, experts and administrations for a sustainable agriculture and rural development, and Joffre et al. (2017), who suggest that aquaculture research and innovation could benefit from management approaches that integrate constant feedback from users.

Most studies in rural areas focus on innovation for a sustainable agriculture. We reviewed them in Section 2.2., but it is worth mentioning here two articles that advocate for the urgent need to renew agriculture's traditional design organization and foster open innovation (Berthet et al., 2018), and identify new approaches towards sustainable agriculture futures, such as agro-ecology, vertical farming, urban agriculture, and digital farming (Pigford et al. (2018). Among the confirming results we obtain, we find Meynard et al. (2017), who observe that firms frequently innovate in one domain in order to adapt to the constraints of another, and call for a renewed research agenda where innovations by agri-food companies come not only on production or on processes, but also organizational and institutional. Indeed, we do observe that product and organisational innovation tend to come together, innovation in processes tend to move inversely, and marketing innovation decisions seem to be independent for agri-food firms. However, these findings dispute the assertion of firms in the agri-food industry being mainly product and process innovation oriented (Batterink et al., 2006).

Faced with that, we obtain some results for agri-food firms for which we cannot trace previous evidence in the literature. These include the distinctive behaviour of marketing innovation that is related to former ICT experience (undermined by the above-mentioned problem with this construct), and a list of determinants of investment decisions to innovate that include internal (firm size, former ICT use) and external factors (seeking new markets, competitive pressure). Finally, our already mentioned inconclusive results on *social* and *value chain* constructs would be in line with Berthet et al. (2018)'s suggestion to orient further opening innovation efforts to building networks.

How do our results compare to others in the literature of SMEs outside rural areas? We get some confirming results. For instance, according to Blanchard et al. (2013), the main barriers to invest in R & D are cost (financial constraints), knowledge (e.g., lack of qualified personnel), and a market dominated by established enterprises. We trace evidence of all of this for t-KIBS firms in rural sectors, where the domain *research* is inversely related to cost and competitors, and positively to employee capabilities. In other instances, our results are inconclusive. For instance, we find no results related to CEO leadership introducing more new products and processes (e.g., Zieba and Zieba, 2014), or Hinrichs et al. (2004)'s finding that innovative marketing at retail farmers' markets is related to social and value chain factors. Indeed, if there is some, we find it only positively related to organisational innovation by t-KIBS. This would be perhaps more in line with authors like Mina et al. (2014), who suggest that institutional partners play a minor role in KIBS R & D activity, though mere access to information provided by universities and research institutions positively influences their innovation.

Before our analysis, we could only trace a couple of research articles on innovation by t-KIBS firms in rural areas. Fernandes et al. (2015) show that KIBS innovation depends on the geographical location in Portugal, with also the evidence that the younger entrepreneur the more probability of KIBS firms locating in rural environments. Teixeira and dos Santos (2016) analyse KIBS in Portugal, and relate innovation to workers' education and to effectively invest in R & D activities – somehow in line with our finding that CEO support in t-KIBS firms comes together with investing in fundamental or applied research. Finally, we could not trace any previous evidence supporting our finding that product innovation by t-KIBS is related to the objective of entering new market niches.

5. Conclusions

By making use of a database that provides information on innovation activities by a large list of Spanish firms, we performed an exploratory analysis on a frequently overlooked area of research: innovation decisions by firms in rural areas. We performed a multivariate statistical analysis based on MCA and PCA combined, to explore the main drivers of innovation by agri-food and t-KIBS firms in rural areas. Using the TOE approach as a conceptual framework, we identify the most relevant factors among a list of 73 indicators in four broad domains, including innovation decisions, organisational, technological and environmental features.

Our results suggest some common factors that appear to be more intensely related to innovation decisions by firms in rural areas, such as internal (firm size, former ICT use) and external factors (seeking new markets, competitive pressure). However, the results suggest as well the usefulness of analysing sectors separately, since some differences may be traced between them. This would support more recent lines of research (e.g., Ettlie and Rosenthal, 2011) compared to earlier literature suggesting innovation factors by farms are similar to other businesses (Lewis, 1998). Two examples of these differences are the distinctive behaviour of marketing innovation by agri-food firms, which would be related to former ICT experience, and that services innovation by t-KIBS would be related to the objective of entering new market niches. Finally, compared to the more extensive literature outside rural areas, we get confirming results such as financial constraints, lack of qualified personnel, and competitors being the main barriers to invest in R & D – here for t-KIBS firms in particular. Moreover, in terms of the negative (Schumpeterian) versus positive (Arrovian) relationship between innovation and competition, our results support the Schumpeterian view for that sort of firms. Nonetheless, our findings dispute some other results – e.g., firms in the agri-food industry being mainly product and process innovation oriented (Batterink et al., 2006) – or are rather inconclusive.

The analysis of innovation by SMEs operating in rural areas has relevant implications for public policy. In many European rural regions, growth prospects are sluggish, due to depopulation and ageing (European Commission, 2013). However, three quarters of the territory are rural areas where more than half of the EU population inhabits, so a sustainable urban development depends on the prosperity of rural areas as well (Hogan, 2016). This gives SMEs operating in rural areas in demographic recession a distinctive profile: firms that depend on internal demand (*residential economy*) face dire perspectives compared to firms in urban areas, while firms that use rural resources to sell outside the rural territory (*productive economy*) might have different reasons to innovate. In this article, we focused on two sectors where firms might easily operate under the productive economy approach. In order to incentive the capacity and intensity of innovation of these types of firms, our results suggest that public policies should pay attention to the main barriers they face (financial constraints, lack of qualified personnel, and uneven market competition), while supporting t-KIBS in their goal of entering new market niches.

However, we must emphasize the limitations of this research. Being an exploratory analysis, we must be aware of the limitations of the statistical techniques used (for instance, summarizing all information of one domain with just one dimension in the MCA treatment). In addition, we were restricted to analyse the variables available in the PITEC database, as well as the small sample of firms that met the rural and sectoral criteria. To overcome these limitations, future research might be based on survey data that allows to getting access to more specific data at the firm level, as well as to better targeting rural areas at a micro level (indeed, in the NUTS 3 regions selected in this research we may still find a dozen cities above 100,000 inhabitants). Nonetheless, the article suggests an open field of research, and the exploratory results obtained might help to better target hypothesis and confirmatory techniques.

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