Exploring the profile of innovative enterprises in high-tech manufacturing sectors: The case of the regions of Madrid and Catalonia in 2016

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This study explores the innovation profiles of Spanish enterprises operating in high-tech manufacturing sectors. Firms with corporate headquarters in one of two prominent regions are considered: Madrid or Catalonia. The innovation profiles describe a firm's capacity to engage in radical, continuous, or no product innovation and represent distinct degrees of innovation performance. They are elaborated by applying two types of discrete choice models: (a) a multinomial logit model, which permits only the estimation of fixed effect parameters, and (b) a flexible mixed-logit model that permits the simultaneous specification of fixed and random parameters. The mixed logit methodology indicates that internal research and development (R&D) funds play no role in innovation in Catalonia. Meanwhile, Madrid-headquartered enterprises are associated with a preference only for incremental rather than radical innovation. The impact of external R&D is significantly more important for Madrid-based firms than for Catalonian ones, but the situation with expenses dedicated to technological development is the reverse. The size of researchers' salaries plays a relevant role in innovation in both regions: in Madrid, radical innovation over incremental innovation and non-innovation are unanimous preferences. However, there are roughly equal chances for both product innovation outcomes in Catalonia. Firm size proves to be a meaningful random variable in relation to innovation performance in both Spanish regions. Concerning its association with the radical/'no innovation' outcome, the results are the same in the focal regions, which display an equal preference for the two choices. Larger size induces Madrid firms to prefer radical innovation to incremental innovation, while Catalonian enterprises consider the latter equally important. Although there is no significant effect in Catalonia, firm size in the Madrid sample is associated with equal preferences for incremental innovation and no product innovation. This study describes firm attributes that enhance product innovation performance in high-tech manufacturing sectors in two distinct regions with above-average within-country per capita gross domestic product (GDP). Methodologically, this shows the importance of using enriched alternative computational approaches, where a mixed logit specification along the multinomial one allows for the simultaneous estimation of fixed- and random-effect parameters in the model, generating additional insight into enterprise attributes regarding the innovation performance phenomena under analysis.

Keywords:
innovation performance,
product innovations,
regional implications,
discrete choice models,
fixed and random parameters

Introduction and literature review

This study's main purpose is to deepen our understanding of the innovation behaviour and performance of Spanish enterprises operating in high-tech manufacturing sectors. In the literature, innovation performance is measured by the propensity of firms to generate product or process innovation (Cohen–Klepper 1996, Klepper–Simmons 2000, Kraft 1990, Broekel–Boschma 2016). Regarding innovation performance, we focus on product innovation. The importance of this type of innovation has been acknowledged in many pieces of academic work. March (1991) considers product innovation activity a means of organisational learning, while Danneels (2002) believes that such activities contribute to developing firm competencies. Scholars have insisted that product innovation facilitates firm renewal and enables firms to gain competitive advantage (Danneels 2002, De Jong–Vermeulen 2006, Klepper–Simmons 2000, March 1991). Product innovation enhances the quality and variety of goods and offers opportunities for enterprise growth in terms of larger quantities and higher prices (Vaona–Pianta 2008). Moreover, researchers have found that introducing product innovation drives process innovation, and that these types of innovation are interdependent (Martinez-Ros 2000, Pisano 1997, Reichstein–Salter 2006). Product innovation is more likely to occur among firms involved in research activities and invest capital in innovation (Roper et al. 2010).

Regarding degrees of novelty, product innovation can be classified into three categories: non-innovation, incremental, and radical innovation. Incremental and radical innovations describe innovation with a low (high) degree of novelty, respectively (Garcia–Calantone 2002, Henderson–Clark 1990, Laursen–Salter 2006). Incremental innovation is a more common phenomenon than radical innovation, perhaps because the latter is riskier and demands more resources (Barbosa et al. 2013). In previous studies (Barbosa et al. 2013, Laursen–Salter 2006), measures of incremental and radical innovation have been constructed based on the distinction between products 'new to the firm' (i.e. introduced by a firm for the first time but not new to the market) and 'new to the market' (i.e. new to the firm and the market). Therefore, our study explores innovation novelty with respect to whether it involves products new to the firm or new to the market (incremental versus radical innovation).

Innovation performance is a result of multiple influencing factors. According to Segarra-Blasco (2010), the probability that a company will engage in product innovation increases with its R&D input (i.e. expenditure), size, and contracting of research staff. As regards input into the innovation process, prior studies have demonstrated the positive influence of R&D investment on product and process innovation (Anzola-Roman et al. 2018, Bhattacharya–Bloch 2004). R&D activities are the most consistent drivers of product innovation and play a critical role in facilitating incremental and radical innovation (Barbosa et al. 2013). As suggested by Jaumandreu (2009), cumulative R&D expenditure determines a major part of productivity and, thereby, the cost advantage of firms.

Santamaría et al. (2009) point out exaggerated attention to the role of R&D activities in innovation studies. The author claims that innovation behaviour also depends on other sources and activities. Various studies have provided evidence that process and product innovation are determined by wages (Flaig–Stadler 1994, Martínez-Ros 2001). Bester–Petrakis (2003) reported that wage rate defines firms' engagement in labour productivity, which affects process innovation. Salaries are positively related to workforce skills and the introduction of new technologies (Bester–Petrakis 2003). Lerner and Wulf (2007) investigate the association between innovation and shifts in the compensation of managers responsible for corporate R&D. Their findings demonstrate that more long-term incentives are associated with frequent awards, heavily cited patents, and patents of greater originality (Lerner–Wulf 2007). Hence, offering long-term incentives to corporate R&D executives leads them to decide better, thereby increasing the productivity of R&D efforts. Shao et al. (2020) found that firms with CEOs who had formerly been engaged in universities or research institutions had better innovation output and performance. Considering the decisive role of research staff in the output of knowledge-based products (Dietz–Bozeman 2005) and the positive connection between salaries and labour productivity (Bester–Petrakis 2003), we aim to investigate the relationship between compensation for researchers and firm innovation. Therefore, we attempt to fill the knowledge gap concerning the lack of understanding of the impact of researchers' salaries on firms' innovation output.

The literature offers mixed findings in terms of firm size and innovation performance. The discussion on the effect of firm size on the effectiveness of innovation is ongoing and requires further elaboration. Several researchers have observed the positive impact of firm size on innovation output (Bhattacharya–Bloch 2004, Cohen–Klepper 1996, Klepper–Simmons 2000), especially in high-technology manufacturing industries associated with a larger share of firms engaged in innovation activity (Minguela-Rata et al. 2014, Santamaría et al. 2009, Segarra-Blasco 2010). The authors suggest that large firms are more inclined to carry out R&D (Arbussà–Coenders 2007) and innovate (Rogers 2004). It is also reported that mostly large incumbent companies engage in major product and process innovation (Klepper–Simmons 2000) owing to their tendency to possess stronger resources and capabilities to dedicate to the innovation process (Barney–Clark 2007). In such companies, there may also be complementarities between R&D and other non-manufacturing activities (Minguela-Rata et al. 2014, Rogers 2004) that help maintain large and diversified innovation portfolios (Van de Vrande et al. 2009) and create value for the R&D pipeline through cooperation with entrepreneurs and suppliers (Brunswicker–Chesbrough 2018).

Firm size appears to be an important determinant of incremental innovation, whereas radical innovation is not affected by firm size (Laursen–Salter 2006). According to the literature (Laursen–Salter 2004, Lee et al. 2010), larger firms are not necessarily better than small and medium-sized enterprises in radical innovation. Large incumbent firms have standardised procedures and routines, whereas small firms tend to be more flexible and creative, especially in highly innovative industries (Audretsch 1995, Giarratana 2004). Small firms often identify business opportunities faster (Harison–Koski 2010), and their key employees can devote more time to innovation-related tasks because of a less rigid management structure (Rogers 2004). In contrast, innovation processes are typically more structured and professionalised in large firms (Van de Vrande et al. 2009). The latter have stronger cash flows dedicated to funding innovation and better access to a wider spectrum of knowledge and human capital skills (Minguela-Rata et al. 2014, Rogers 2004). Hence, the contradictory results documented in innovation literature motivate us to examine the effect of company size on innovation activity.

The propensity to implement any innovation activity varies across sectors, although the link between innovation and science is explicit and direct in some industries (e.g. biotechnology and pharmaceuticals). Firms operating in knowledge- and technology-intensive industries are more likely to actively undertake R&D than firms in low-technology and service sectors (Arbussà–Coenders 2007). As Van de Vrande (2009) noted, manufacturing firms are more technology-intensive and invest significantly in R&D.

Some authors have found that major product innovations are likely to emerge in manufacturing companies located in larger cities (Shearmur 2011, Van de Vrande 2009). An early study found that enterprises require a larger and denser regional environment for product development (Karlsson–Olsson 1998). Alcácer (2006) argued that agglomeration stimulates R&D activities due to knowledge spillovers. For example, organisational proximity is the most important determinant of multinational enterprises' co-location across high research-intensive and science-based industries. Companies can benefit from collaboration and knowledge sharing (Le Duc–Lindeque 2018, Sebestyén et al 2021). Different regions may have different traits regarding their populations' innovation habits (Kourtit et al. 2012). Moreover, the regional industry structure plays a moderating role in the association between R&D investment and innovation performance (Aarstad–Kvitastein 2019). Many studies on innovation have addressed the innovation patterns of firms in different countries (Alcácer 2006, Páthy 2017, Roper et al. 2010, Sebrek 2020, Zdanowska et al. 2020), although considerable variation in innovation activity can occur among regions within the same country (Almeida–Kogut 1999, Buesa et al. 2006, Páthy 2017). Therefore, we argue that location may affect firms' innovation behaviour. The relationships between specific areas within a single country and the innovation profiles of enterprises should be studied further.

We restricted our analysis to firms in the high-technology manufacturing sector in Spain. This country offers a large sample of such firms and provides an interesting research setting as one of the countries of the European Union with greater regional diversity (European Commission 2013). Spanish regions have diverse economies with varying degrees of innovation performance. Regional authorities have developed their scientific, technological, and innovation policies associated with significant budgets for financing and promoting R&D and innovation (Cruz-Castro et al. 2018). As the separation of samples can enable a more fine-grained analysis of innovation determinants (as opposed to a single sample), we select two major industrial regions in Spain: Madrid and Catalonia.

Madrid was chosen because it has a complete innovation system than other regions (Buesa et al. 2006). The capital city of Spain, Madrid, is one of the most economically dynamic cities in the region, with a vibrant community of engineering professionals and supporting occupational institutions (Rama et al. 2003). The geographical proximity of firms in Madrid facilitates industrial, scientific, and technical cooperation (Sánchez Moral 2009). The commitment of Catalan firms to R&D activities has been stronger than in the rest of Spain (Segarra-Blasco 2010), and its manufacturing base is substantial in (relative) regional and national comparisons (Roper et al. 2010), with a remarkable share of high-technology products (Directorate-General for Economic Analysis 2020). Catalonia has an outstanding research infrastructure and hosts the most innovative companies in Spain.

In summary, we investigated the profile of innovative firms in terms of the degree of novelty in the high-tech manufacturing sector. The aim was to explore the propensity for product innovation in relation to firms' geographical location and firm-specific characteristics (e.g. R&D expenses, size, and researchers' salaries). The methodological approach used in this study was to apply two discrete choice models: a logit model and a mixed logit model (McFadden–Train 2000, Train 2003, Cao 2021, Fouded 2021). As Barbosa et al. (2013) noted, discrete choice models are the best approach to assess the impact of a firm's innovation choices on innovation novelty. Researchers may be able to conduct methodologically more effective studies in regional statistics using these models. They can adapt flexible computational approaches, such as the mixed logit specification, which facilitates the simultaneous estimation of fixed- and random-effect parameters in their models. Consequently, additional insights can be obtained regarding the attributes of the studied phenomena.

The remainder of this paper is organised as follows. The next section provides a detailed description of the Spanish dataset used in the investigation, the two regions examined, and the variables incorporated into the analyses. The third section discusses the notion of discrete choice models, focusing on multinomial and mixed logit models. The following section reports empirical evidence on firm innovation performance in the two regions, given the distinct methodologies. The final section summarises the main conclusions.

Dataset and variables

Our data are sourced from the Technological Innovation Panel (PITEC) database constructed by the Spanish National Statistics Institute (INE), which has been extensively exploited in computational-intensive articles (Barge-Gil 2010, Escribano et al. 2009, Sebrek–Pérez 2015). The data cover an extensive sample of Spanish enterprises, providing information about their innovation processes, attributes, and developmental indicators. This study used data from 2016 (the last year of the database), containing 12,849 firms. Two filters were used in the study. First, we selected firms from high-tech manufacturing sectors (variable in PITEC: *actin*) reducing our sample to 323 firms. Second, we selected firms with corporate headquarters located in Madrid or Catalonia (variable in PITEC: *sede*), reducing our final sample to 212 firms. The selected data are summarised in Table 1.

Table 1

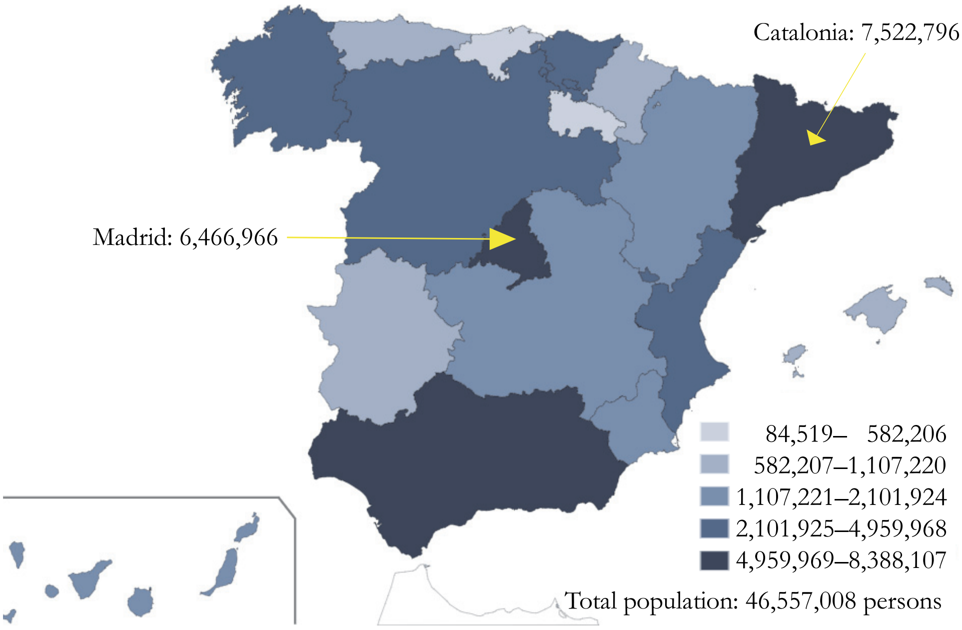
Data selection, 2016

PITEC (*actin*)	CNAE2009	Industry	Classification	Headquarters (*sede*) in Madrid	Headquarters (*sede*) in Catalonia
0011	21	Manufacturing of pharmaceutical products	high-tech	33	71
0016	26	Manufacturing of computer, electronic, and optical products	high-tech	49	55
0021	303	Aeronautic and spatial construction	high-tech	4	0
			Subtotal	86	126
			Total sample	212	

Spain is divided into 17 autonomous communities that provide significant political and fiscal autonomy to regional governments (Cruz-Castro et al. 2018). Figure 1 displays the graphical location and total population of Madrid and Catalan's selected autonomous communities. Table 2 reveals the additional socioeconomic indicators for Spain and the target regions.

Figure 1

Total population in 2016: Madrid and Catalonia



Source: Spanish National Statistics Institute (INE).

Table 2

Socioeconomic indicators in 2016

Indicator	Spain	Madrid	Catalonia
Population, people	46,557,008	6,466,996	7,522,596
Territory, km^2	505,944	8,028	32,113
Population density, people per km^2	92	806	234
GDP, million EUR	1,232,570	211,673	212,704
Per capita GDP, EUR	26,474.4	32,731.3	28,275.3

Dependent variable

The dependent variable (DV) represents the sampled firms' product innovation performance. PITEC data report whether a firm created no new products, undertook incremental innovation involving novelty exclusive to the firm, or engaged in radical innovation, indicating the firm's ability to create products new to the world market, thus representing the highest level of performance (Laursen–Salter 2006). Prior studies have attempted to explore the different degrees of novelty attached to the innovation process (Freeman–Soete 1997, Laursen–Salter 2006). Two major innovation types are differentiated (Garcia–Calantone 2002, Henderson–Clark 1990): incremental innovation (e.g. the release of a new version of a pre-existing software product) and radical innovation (e.g. fully electric Tesla cars with ample range).

Table 3

Dependent variable representing the organisational level of innovation, 2016

Variable	Description	Details
novedademp (original)	If the product innovation is new to the firm	1 = yes, 0 = no
novedad (original)	If the product innovation is new to the market	1 = yes, 0 = no
noinn (created)	Firms without product innovation	*novedademp* = 0 and *novedad* = 0
newtofirm (created)	Firms with product innovation with novelty at firm level	*novedademp* = 1 and *novedad* = 0
newtomarket (created)	Firms with product innovation with novelty at market level	*novedademp* = 1 and *novedad* = 1 or *novedademp* = 0 and *novedad* = 1

The variable is created using two proxies, as listed in Table 3. In our research context, *novedademp* symbolises a firm's ability to engage in product innovation that is new to the firm and thus can be considered incremental innovation. *Novedad* indicates the ability of a firm to engage in radical innovation, defined as innovation embedded into a product that is new to the world market. Radical innovation has been deemed competence-destroying for incumbent companies and greatly alters patterns of competition within the respective industrial fields (Tushman–Anderson 1986, Anderson–Tushman 1990). In addition, radical innovation is less common than incremental innovation and generates greater rewards (Marsili–Salter 2005). Therefore, *novedad* implies greater innovation performance than *novedademp* (Laursen–Salter 2006).

We constructed three categories, representing three levels of product innovation: firms without product innovation and firms that launched novel products at the firm or market level. Table 3 summarises the sources and construction of DV.

A multinomial logit model was selected because DV contains more than two categories. This permits a pairwise comparison of the three outcomes, requiring the three regression models to run. We compared *newtomarket* to *newtofirm* (Model 1), *noinn* to *newtofirm* (Model 2), and *newtomarket* to *noinn* (Model 3).

Independent variables

The profile of enterprises was explored based on five attributes or independent variables (IVs). The first two attributes are related to innovation expenditure. The first one (*intr&d*) shows the proportion of innovation expenditure dedicated to internal R&D activities. The second (*extr&d*) is the proportion assigned to external R&D activities. The third attribute (*ressalary*) reflects the proportion of internal R&D expenses dedicated to researchers' salaries. Fourth (*techdev*) measures technological development associated with the proportion of current expenses allocated to technological development activities by firm administration. Finally, the last attribute (*firmsize*) reflects firm size expressed by the number of employees. Table 4 summarises the IVs used in this study, aimed at capturing certain attributes of the sampled firms.

Table 4

List of independent variables

Name of variable	Original variable name in PITEC	Description	Details
intr&d	*gintid*	Internal R&D expenditure	Proportion of innovation expenditure dedicated to internal R&D activities
extr&d	*gextid*	External R&D expenditure	Proportion of innovation expenditure dedicated to external R&D activities
ressalary	*reci*	Salaries for researchers	Proportion of internal R&D expenses dedicated to salaries for researchers.
techdev	*destec*	Technological development	Measure of technological development
firmsize	*tamano*	Firm size	Integer value

Discrete choice models

This section presents the statistical background of the two selected discrete choice models: the multinomial logit model and mixed logit model. The last part of this section describes the underlying differences between the two approaches.

The multinomial logit model

Considering random utility theory, let us assume that firm *i* obtains a certain level of utility by choosing the level of innovation *a,* expressed as:

$$U_{ia} \ = \ \boldsymbol{\beta}_i^T \boldsymbol{X}_{ia} + \varepsilon_{ia}\,,\ i=1,..,I, \quad a = \{noinn,\ newtofirm,\ newtomarket\}, \tag{1}$$

where $\boldsymbol{X}_{ia}$ is a (z × 1) vector of observed variables that captures the attributes of the firms denoted in our study as: *intr&d*, *extr&d*, *ressalary*, *techdev* and *firmsize*. $\boldsymbol{\beta}_z^T$ is a (1 × z) vector of the coefficients of these attributes and ε_{ia} is the random error. Under the assumption of firms' utility-maximisation behaviour, the probability that firm *i* will choose alternative *k* is given by:

$$\pi_{ik} = \text{Prob}(U_{ik} > U_{ia},\ \text{for all}\ a \neq k)$$

The expression above indicates that firm *i* selects the level of innovation *k* because this alternative provides the greatest utility. Thus, it can be rewritten as:

$$\begin{aligned}\pi_{ik} &= \text{Prob}(\boldsymbol{\beta}_i^T \boldsymbol{X}_{ik} + \varepsilon_{ik} > \boldsymbol{\beta}_i^T \boldsymbol{X}_{ia} + \varepsilon_{ia},\ \text{for all}\ a \neq k) \\ &= \text{Prob}(\varepsilon_{ia} - \varepsilon_{ik} < \boldsymbol{\beta}_i^T \boldsymbol{X}_{ik} - \boldsymbol{\beta}_i^T \boldsymbol{X}_{ia},\ \text{for all}\ a \neq k)\end{aligned}$$

Note that the probability of choosing the level of innovation *k* is the cumulative probability that each random term $(\varepsilon_{ia} - \varepsilon_{ik})$ is less than the observed quantity $(\boldsymbol{\beta}_i^T \boldsymbol{X}_{ik} - \boldsymbol{\beta}_i^T \boldsymbol{X}_{ia})$.

Denoting the density function of the error term as $f(\varepsilon_i)$, the probability of choosing the level of innovation *k* can be written as

$$\pi_{ik} = \int_{\varepsilon} I(\varepsilon_{ia} - \varepsilon_{ik} < \boldsymbol{\beta}_i^T \boldsymbol{X}_{ik} - \boldsymbol{\beta}_i^T \boldsymbol{X}_{ia},\ \text{for all}\ a \neq k) \cdot f(\varepsilon_i)\, \delta\varepsilon_i \tag{2}$$

where $I(\cdot)$ is the indicator function.

The multinomial logit model assumes that $\boldsymbol{\beta}$ does not vary across firms and that each error ε_i is independently and identically distributed following a Gumbel distribution (or type I extreme value). Under these assumptions, the resulting integral has a closed-form expression, and the probability of choosing the level of innovation *k* can be written as

$$\pi_{ik} = \frac{e^{\boldsymbol{\beta}^T \boldsymbol{X}_{ik}}}{\sum_{a=1}^{A} e^{\boldsymbol{\beta}^T \boldsymbol{X}_{ia}}} \tag{3}$$

which is called the logit choice probability. The multinomial logit model permits the estimation of homogeneous preferences through fixed-effect parameters.

Mixed logit models

Mixed logit models can be derived in various ways, with each derivation providing a particular interpretation (Train 2003). This model is more flexible because it allows the simultaneous estimation of homogeneous preferences by introducing fixed effects to the model and the estimation of heterogeneous preferences via the introduction of random effect parameters in the model. Three main steps are involved in testing the significance of the random-effects parameters in the model. First, it is necessary to specify the potential distribution of random effects (e.g. normal distribution, lognormal distribution). Second, estimate the model including the proposed random effects. Third, verify whether the random effects are significant in the model.

For instance, consider the case of a mixed logit model with a single random effect β_z . In the first step, we specify the potential distribution of the random effect. For example, we can assume that it follows a normal distribution, $\beta_z \sim N(\mu, \sigma^2)$. Second, we estimate the model, including the proposed random effect β_z . Third, we verify whether the proposed random effect β_z , is significant in the model. To do this, it is necessary to check whether the estimated standard deviation of the random effect $\hat{\sigma}$, is significant. If so, then the random effect β_z is significant in the model.

The interpretation of random effects provides useful information during the analysis. Considering our previous example, estimating the random effect $\hat{\beta}_z$ allows us to determine the proportion of firms with a positive (or negative) coefficient. For instance, if the estimated random effect is $\hat{\beta}_z \sim N(\hat{\mu}, \hat{\sigma}^2)$, then the share of firms with a negative coefficient (i.e. negative $\hat{\beta}_z$) can be calculated as

$$P(X \leq 0) = P\left(\frac{X - \hat{\mu}}{\hat{\sigma}} \leq -\frac{\hat{\mu}}{\hat{\sigma}}\right) = P\left(Z \leq -\frac{\hat{\mu}}{\hat{\sigma}}\right), \tag{4}$$

where Z is the standardised normal distribution. In contrast, the share of firms with a positive coefficient (i.e. positive $\hat{\beta}_z$) can be calculated as

$$P(X \geq 0) = 1 - P(X \leq 0) \tag{5}$$

Under the assumptions of this fixed-logit model, the probability of choosing alternative *k* is given by the following expression:

$$\pi_{ijk} = \int \left(\frac{e^{\boldsymbol{\beta}_z^T \boldsymbol{X}_{zijk}}}{\sum_{a=1}^{A} e^{\boldsymbol{\beta}_z^T \boldsymbol{X}_{zija}}} \right) f(\boldsymbol{\beta}|\theta)\, d\boldsymbol{\beta}, \tag{6}$$

where the integral does not have a closed form and must be approximated using numerical methods.

Goodness-of-fit tests

There are different measures to assess the goodness of fit of the logistic regression models. In this study, we used two of these methods. The first measure is the likelihood ratio test, defined as:

$$LR = 2\left(LL(0) - LL(\hat{\beta})\right) \tag{7}$$

where $LL(\hat{\beta})$ is the log-likelihood of the proposed model and $LL(0)$ is the log-likelihood of the model with only an intercept as a predictor (null model). If this difference is statistically significant, the proposed model performs significantly better than the null model does.

The second measure is the McFadden pseudo R^2, defined as

$$R^2_{\text{McFadden}} = 1 - \frac{LL(\hat{\beta})}{LL(0)} \quad (8)$$

According to McFadden (1979), if the resulting value ranges from 0.2 to 0.4, it indicates a good fit.

Comparison and limitations of both methodologies

There is an important difference between the multinomial logit model and the mixed logit model, arising from their capacity to capture the behaviour of firms. The multinomial logit model assumes that all firms share homogeneous preferences and captures these preferences through fixed effects parameters. Thus, an inherent limitation of this approach is that it cannot capture the possible heterogeneity among firms. However, the mixed logit model obviates the three limitations of standard logit models by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Train 2003). Moreover, it permits the simultaneous capture of homogeneous preferences (through fixed effects) and heterogeneous preferences (through random effects). Considering that the behaviour of firms is not known in advance, we considered it important to explore both approaches.

It is at the researcher's discretion to specify a given variable as a fixed or random parameter or decide upon the latter's distribution (Train 2003). A body of literature emphasises that the scientific activity of research staff (Giarratana 2004, Lazerson 1988, Sebrek 2020, Spithoven et al. 2010) and organisational size (Greve 2011, Li et al. 2020, Rothaermel–Deeds 2004) can contribute to firm success with regard to certain elements of strategic change. We decided to define *ressalary* and *firmsize* as random variables.

Findings and discussion

This section explores the profile of Spanish enterprises considering the location of their corporate headquarters, namely Madrid and Catalonia. Each profile was analysed using two methodological approaches: a multinomial logit model and a mixed logit model. The results of this study were obtained using the *mlogit* package in the statistical software *R* (Croissant 2020, R core team 2022).

Profile of enterprises in Madrid

The profile of enterprises located in Madrid was created on 86 firms. Table 5 presents the basic statistics of the IVs for the entire sample and distinct categories of DV.

Table 5

Descriptive statistics for firms in the Madrid sample, 2016

IVs	Full sample		DV: *noinn*		DV: *newtofirm*		DV: *newtomarket*	
	mean	sd	mean	sd	mean	sd	mean	sd
intr&d	60.35	41.87	41.81	46.54	72.77	39.23	68.54	33.69
extr&d	7.24	18.39	3.88	11.02	3.45	16.25	12.93	23.51
ressalary	32.98	32.43	10.98	17.81	44.67	37.35	44.82	29.15
techdev	35.01	41.85	19.57	35.67	39.13	44.94	46.18	41.79
firmsize	247	471.8	159.37	180.43	74.65	100.47	446.79	696.5

Notes: sd: standard deviation.
Variable definition:
intr&d: proportion of innovation expenditure dedicated to internal R&D activity.
extr&d: proportion of innovation expenditure dedicated to external R&D activity.
ressalary: proportion of internal R&D expenses dedicated to salaries for researchers.
techdev: measure of technological development.
firmsize: size of firm.

On average, the proportion of innovation expenditure dedicated to internal R&D activities (variable: *intr&d*) is smaller in firms without product innovation (41.81%) and larger in firms with product innovation at either the *newtofirm* or *newtomarket* level (72.77% and 68.54%, respectively). The proportion of innovation expenditure dedicated to external R&D activities (variable: *extr&d*) is larger in firms with product innovations at the *newtomarket* level (12.93%) contrasted with the other two DVs. Regarding the average proportion dedicated to salaries for researchers (variable: *ressalary*), this quantity is similar in firms with product innovation at either the *newtofirm* or *newtomarket* levels (44.67% and 44.82%, respectively), which proves to be much greater than the value of non-innovating enterprises. On average, technological development (*techdev*) increases as firms become more innovative. Finally, firm size (variable: *firmsize*) is prominently larger in firms with product innovations at the *newtomarket* level (on average, 447 employees) compared to the two other outcomes. Table 6 lists the correlation matrices of the IVs.

Table 6

Correlation matrix and basic statistics for firms in the Madrid sample, 2016

	intr&d	*extr&d*	*ressalary*	*techdev*	*firmsize*
intr&d	1				
extr&d	–0.19	1			
ressalary	0.56	–0.11	1		
techdev	0.48	–0.09	0.51	1	
firmsize	0.11	0.22	0.02	0.19	1
mean	60.35	7.24	32.98	35.01	247
sd	41.87	18.39	32.43	41.85	471.8
minimum	0	0	0	0	1
maximum	100	100	98.5	100	2,764

Note: See Table 5 for a description of the variables.

Table 6 shows a moderate positive correlation between the attributes *ressalary* and *intr&d* (0.56) and the attributes *techdev* and *ressalary* (0.51). In the rest of the cases, the correlation is less than 0.5.

In the following section, we describe the profile of firms using two methodological approaches. The first approach involves using a multinomial logit model, wherein firms are assumed to share homogeneous preferences and capture them through the fixed effects parameters. Because the DV in our study contains three categories, it is necessary to estimate three models to compare these categories appropriately. Table 7 presents the results of the estimated multinomial logit model for the three models. First, we estimate Model 1 to compare *newtomarket* with *newtofirm* as a reference group category, while in Model 2, we compare *noinn* with *newtofirm* as the base category. Model 3 estimates *newtomarket* by applying the reference group category *noinn*.

Table 7

Profile of innovative enterprises in Madrid using the classical approach: multinomial logit model, 2016

DV	Model 1 **newtomarket**		Model 2 **noinn**		Model 3 **newtomarket**	
Reference group	*newtofirm*		*newtofirm*		*noinn*	
	estimate	sd	estimate	sd	estimate	sd
Fixed effects						
intercept	–0.768	0.78	**1.13**	0.55*	**–1.897**	0.66**
intr&d	–0.005	0.01	–0.006	0.01	0.001	0.01
extr&d	0.013	0.02	–0.019	0.03	**0.032**	0.02*
ressalary	0.01	0.01	**–0.044**	0.02*	**0.054**	0.02**
techdev	0.002	0.01	0.004	0.01	–0.002	0.01
firmsize	**0.006**	0.00*	0.004	0.00	0.001	0.01

Notes: *** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05, † p-value < 0.1. Sd: standard deviation. See Table 5 for a description of the variables. McFadden R^2: 0.247. Likelihood ratio test: chisq = 46.223 (p-value = 1.307e-06).

The results show that the intercept is significant in Models 2 and 3, demonstrating firms' inertia regarding engagement in any product innovation. External R&D expenditure has a positive and 10% significant effect in Model 3. This means that an additional unit increases the probability by 0.032, thus enhancing the likelihood of firm innovation at the *newtomarket* level compared to the *noinn* level, indicating a clear preference for radical innovation rather than an inert innovation enterprise posture.

The expenditure dedicated to salaries for researchers (*ressalary*) is significant in Models 2 and 3. In both cases, the interpretation is that: firms become more innovative as the magnitude of enterprise expenses dedicated to researchers increases. In Model 2, it increases the probability at the *newtofirm* level compared to *noinn*, while in Model 3, it increases the probability of firms' classification as *newtomarket* vis-à-vis *noinn*. Finally, firm size has a positive significant effect in Model 1: each additional unit of *firmsize* increases the probability by 0.006, expressing the link between firm size and *newtomarket* status versus *newtofirm*. In other words, large firms are more likely to present radical innovations than incremental innovations. Regarding the significance of the multinomial logit model, the p-value of the likelihood ratio test is 1.3065e-06, indicating that the model is statistically significant. Similarly, the McFadden pseudo R^2 value indicated a good fit (0.247).

The second approach to exploring the profile of firms assumes heterogeneous preferences in one or more attributes, thereby specifying the random effects in the model. Table 8 presents the results of the mixed logit model and incorporates two random effects through the variables *ressalary* and *firmsize*.

Table 8

Profile of innovative enterprises in Madrid using the mixed logit model, 2016

DV		Model 1 **newtomarket**		Model 2 **noinn**		Model 3 **newtomarket**	
Reference group		*newtofirm*		*newtofirm*		*noinn*	
		estimate	sd	estimate	sd	estimate	sd
				Fixed effects			
intercept		**–7.792**	1.23***	2.304	3.10	**–4.210**	1.05***
intr&d		**–0.157**	0.08†	0.094	0.14	–0.164	0.11
extr&d		**0.233**	0.07***	**–0.362**	0.15*	0.224	0.40
techdev		0.016	0.05	**0.250**	0.11*	–0.110	0.15
				Random effects			
ressalary	mean	**0.393**	0.09***	**–1.387**	0.58*	**0.948**	**0.41***
	sd	0.565	0.42	0.396	0.89	**–**0.611	0.56
firmsize	mean	**0.221**	0.00***	0.103	0.10	**–**0.031	0.05
	sd	**0.229**	0.00***	**0.687**	0.12***	**0.145**	**0.06***

Notes: *** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05, † p-value < 0.1. Sd: standard deviation. See Table 5 for a description of the variables. McFadden R^2: 0.154. Likelihood ratio test: chisq = 28.737 (p-value = 0.011).

The first part of Table 8 estimates the fixed effect parameters. The intercept has a significant negative effect in Models 1 and 3, delineating a more nuanced picture than before. Firms in the Madrid sample refrain from innovating products new to the world market and prefer either incremental innovation or not to be innovative. Internal R&D expenditure is negative and significant on the margin in Model 1; in this case, augmenting internal R&D decreases the probability by 0.157 that firms engage in *newtomarket* innovation compared to *newtofirm* innovation. In other words, possessing more resources for internal R&D increases the probability of less radical product innovation.

External R&D expenditures are significant in Models 1 and 2. In both cases, firms become more innovative as external R&D expenditures rise. In Model 1 (2), the variable increases the probability that a firm engages in *newtomarket* (*newtofirm*) innovation rather than *newtofirm (noinn*) innovation.

The measure of technological development is positive and significant in Model 2: adding one additional unit of *techdev* increases the relative log odds by 0.250, increasing the probability that firm innovation can be classified as *noinn* instead of *newtofirm*. The results suggest that when firms allocate a greater proportion of their current expenses to technological development, they are less likely to engage in incremental product innovation. We speculate that this is because of the need to avoid attentional overload during business administration.

Finally, the second part of Table 8 estimates the proposed random effects parameters *ressalary* and *firmsize*. We assume that they follow a normal distribution in both cases, delivering the estimation of $\hat{\beta}_{ressalary}\ N(\hat{\mu}_{ressalary}, \hat{\sigma}^2_{ressalary})$ and $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize}, \hat{\sigma}^2_{firmsize})$, respectively.

In the case of the first random effect, $\hat{\beta}_{ressalary}$, the results show that only the mean, $\hat{\mu}_{ressalary}$, is significant in all models, meaning that there is no evidence that $\hat{\beta}_{ressalary}$ is a normally distributed random variable. More researchers on payroll indicate that radical innovation is preferred to incremental and no innovation and that incremental innovation is strictly preferred to no product innovation.

By contrast, concerning the second random effect, $\hat{\beta}_{firmsize}$, the standard deviation, $\hat{\sigma}_{firmsize}$, is significant in all models, meaning that there is statistical evidence that $\hat{\beta}_{firmsize}$ is a random effect normally distributed in every model. In Models 2 and 3, the estimated distributions were $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize} = 0, \hat{\sigma}^2_{firmsize} = 0.687^2)$ and $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize} = 0, \hat{\sigma}^2_{firmsize} = 0.145^2)$, respectively. In both cases, the centre of the distribution is zero ($\hat{\mu}_{firmsize} = 0$), meaning that for approximately 50% of the firms, the estimated coefficient $\hat{\beta}_{firmsize}$ is positive, and for the rest (that is, 50% of the firms), it is negative. Using the random parameter *firmsize*, these results imply that firms in Madrid prefer incremental and no innovation (Model 2 in Table 8) and radical and no product innovation (Model 3 in Table 8) equally.

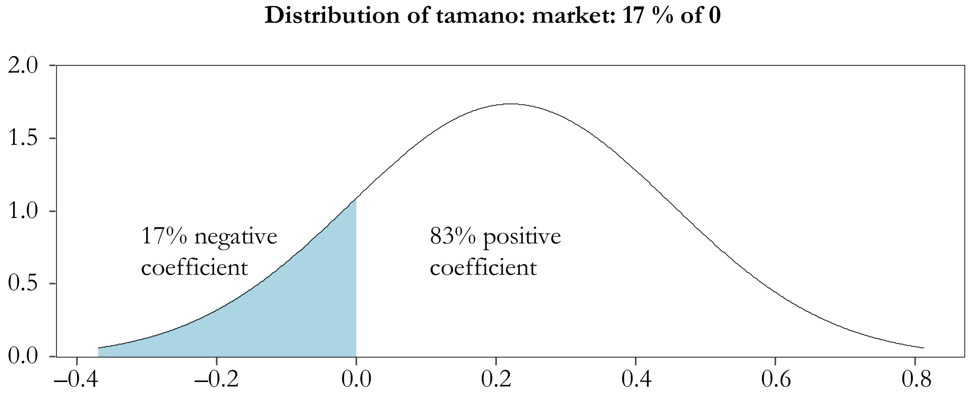
In Model 1, the estimated distribution is $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize} = 0.221, \hat{\sigma}^2_{firmsize} = 0.229^2)$. The distribution centre is different from zero ($\hat{\mu}_{tamano} = 0.221$), requiring an additional calculation to establish the proportion of firms with positive and negative coefficients. The following simple equation gives the proportion of firms with a negative coefficient:

$$P(X \leq 0) = P\left(\frac{X - 0.221}{0.229} \leq -\frac{0.221}{0.229}\right) = P\left(Z \leq -\frac{0.221}{0.229}\right) = P(Z \leq -0.967) \approx 0.17\ .$$

For approximately 17% of firms, the effect of firm size, through the negative coefficient, increases the probability of innovation of the *newtofirm* type compared to *newtomarket*. For the remaining firms (i.e. 83%), it augments the probability (positive coefficient) of innovation at the *newtomarket* level compared to the *newtofirm* level. Consequently, one can conclude that the average-sized firm in Madrid unequivocally prefers radical innovation vis-à-vis incremental innovation. However, the preference is the reverse for almost one-fifth of the firm population. Figure 2 displays the distribution of the random effect $\hat{\beta}_{firmsize}$ in Model 1.

Figure 2

Distribution of the random effect $\boldsymbol{\hat{\beta}_{firmsize}}$ for the Madrid sample in 2016



Note: the random effect comes from Model 1 of Table 8.

Concerning the significance of the mixed logit model, the results show that the p-value of the likelihood ratio test is 0.011, meaning that the model is statistically significant, as confirmed by the McFadden pseudo R^2 (0.154), which indicates a good fit.

Regarding the two methodological approaches, we conclude that a mixed logit model provides a more thorough assessment of the profile of innovating enterprises than a traditional multinomial logit model. This facilitates the identification of heterogeneous features through more variables that reach conventional significance levels in relation to fixed and random effects.

Profile of enterprises in Catalonia

In the case of Catalonia, firm profiles were analysed based on a sample of 126 firms. Table 9 presents the basic statistics of the IVs for the entire sample and the distinct categories of DV.

On average, the proportion of innovation expenditure dedicated to internal R&D activities (variable: *intr&d*) increases as firms become more innovative. The proportion of innovation expenditure dedicated to external R&D activities (variable: *extr&d*) is similar in all categories, varying from 9.56% to 11%. On average, salaries dedicated to researchers (variable: *ressalary*) increase in terms of innovation performance and are the highest in firms with radical product innovation (36.30%). The measure of technological development (variable: *techdev*) grows with innovation performance, reaching a peak at *newtomarket* level (47.49%). The firm size covariate reaches its highest value with 'radical innovation' (342), substantially higher than its value for *noinn* (126.04) or *newtofirm* (143.21). One can identify major differences between the samples from Madrid and Catalonia through descriptive statistics: firms in Madrid allocate more of their current expenses to researchers' salaries for effective product innovation activity than those in Catalonia and are larger in size. Table 10 presents the correlation matrices of IVs.

Table 9

Descriptive statistics for firms in the Catalonian sample, 2016

IVs	Full sample		DV: *noinn*		DV: *newtofirm*		DV: *newtomarket*	
	mean	sd	mean	sd	mean	sd	mean	sd
intr&d	54.84	41.63	36.85	43.75	62.23	41.31	68.61	32.40
extr&d	10.47	20.83	11.00	23.23	9.56	22.25	10.58	17.18
ressalary	30.17	29.53	24.16	32.60	30.53	27.49	36.30	26.72
techdev	32.35	38.27	12.23	27.93	40.97	37.52	47.49	39.66
firmsize	207.67	322.52	126.04	252.13	143.21	202.01	342.0	411.2

Notes: sd: standard deviation. See Table 5 for a description of the variables.

The correlation matrix shows a moderate positive correlation between the variables *ressalary* and *intr&d* (0.64), and between *techdev* and *intr&d* (0.53); for the rest, the correlation is less than 0.5.

Table 10

Correlation matrix and basic statistics for firms in the Catalonian sample, 2016

	intr&d	*extr&d*	*ressalary*	*techdev*	*firmsize*
intr&d	1				
extr&d	–0.14	1			
ressalary	0.64	0.07	1		
techdev	0.53	–0.11	0.34	1	
firmsize	0.06	0.25	0.01	0.06	1
mean	54.84	10.47	30.17	32.35	207.67
sd	41.63	20.83	29.53	38.27	322.52
minimum	0	0	0	0	1
maximum	100	100	97.1	100	1,424

Note: See Table 5 for a description of the variables.

Table 11 presents the first approach to exploring the profiles of firms, assuming that all share homogeneous preferences for every attribute. Similar to the Madrid case, this table presents the results of three models with the same construction.

Table 11

Profile of innovative enterprises in Catalonia using the classical approach: multinomial logit model, fixed effects in 2016

DV Reference group	Model 1 ***newtomarket***		Model 2 ***noinn***		Model 3 ***newtomarket***	
	newtofirm		*newtofirm*		*noinn*	
	estimate	sd	estimate	sd	estimate	sd
intercept	–0.539	0.56	**1.153**	0.42**	**–1.691**	0.49**
intr&d	0.000	0.01	–0.012	0.01	0.012	0.01
extr&d	–0.005	0.01	–0.002	0.01	–0.004	0.01
ressalary	0.008	0.01	0.014	0.01	–0.007	0.01
techdev	0.003	0.01	**–0.022**	0.01**	**0.025**	0.01**
firmsize	**0.002**	0.00*	0.000	0.00	**0.002**	0.00*

Notes: *** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05, † p-value < 0.1. Sd: standard deviation. See Table 5 for a description of the variables. McFadden R^2: 0.148. Likelihood ratio test: chisq = 40.492 (p-value = 1.388e-05).

The results show that the intercept is significant in Models 2 and 3, demonstrating firms' inertia about managing any type of innovation, similar to the firms in the Madrid sample. The measure of technological development (*techdev*) was significant in Models 2 and 3. As Catalonian enterprises increased their technological development, they became more innovative in both cases. Specifically, in Model 2 (3), the variable increases the probability that incremental (radical) innovation will be selected compared with an inert innovation posture.

Finally, firm (*firmsize*) has a positive significant effect in Models 1 and 3. In both cases, firms become more innovative because of increased *firmsize*. Specifically, in Model 1, the variable increases the probability of firms adopting a *newtomarket* innovation approach rather than a *newtofirm* one. In Model 3, *firmsize* strengthens the probability of selecting a *newtomarket* strategy rather than a *noinn* strategy. Hence, larger firms unilaterally prefer new-to-the-market innovations vis-à-vis new-to-the-firm ones or no innovation. The p-value of the likelihood ratio test (1.388e-05) and McFadden pseudo R^2 (0.148) indicate the significance of the multinomial logit model.

The last approach assumes heterogeneous preferences for one or more attributes (IVs). Table 12 presents the results of the mixed logit model for the Catalonian enterprise population, including two random effects: *ressalary* and *firmsize*.

Regarding the fixed effects in Table 12, the intercept is significant in all models, signifying that firms in each outcome pair do not engage in sophisticated innovation. External R&D expenditure is negative and significant in Model 3. Adding one additional unit decreases the probability of radical innovation by 0.182, whereby sufficiently non-incentivising the firms to select *newtomarket* vis-à-vis *noinn* level.

Table 12

Profile of innovative enterprises in Catalonia using the mixed logit model, 2016

DV		Model 1 ***newtomarket***		Model 2 ***noinn***		Model 3 ***newtomarket***	
Reference group		*newtofirm*		*newtofirm*		*noinn*	
		estimate	sd	estimate	sd	estimate	sd
				Fixed effects			
intercept		**–9.468**	5.07†	**1.883**	0.90*	**–10.844**	4.82*
intr&d		–0.028	0.02	–0.004	0.04	–0.004	0.02
extr&d		–0.095	0.08	0.012	0.09	**–0.182**	0.04***
techdev		**0.124**	0.03***	–0.165	0.15	**0.179**	0.02***
				Random effects			
ressalary	mean	–0.046	0.06	0.172	0.18	**–0.067**	0.03*
	sd	**0.977**	0.18***	0.193	0.22	**0.590**	0.35†
firmsize	mean	0.006	0.01	0.020	0.03	**0.012**	0.01*
	sd	**0.380**	0.02***	0.133	0.10	**0.400**	0.01***

Notes: *** p-value < 0.001, ** p-value < 0.01, * p-value < 0.05, † p-value < 0.1. Sd: standard deviation. See Table 5 for a description of the variables. McFadden R^2: 0.1359. Likelihood ratio test: chisq = 37.202 (p-value = 0.0006875).

Technological development had a positive and significant effect in Models 1 and 3. In both cases, firms become more innovative as their degree of technological development increases. Specifically, the variable increases the probability that firms engage in *newtomarket-type innovation* compared to *newtofirm* and *noinn*. Hence, for firms that dedicate a greater than average amount of funds toward technological development, the creation of innovations with novelty in relation to the entire market is preferred over the two other outcomes.

Following an examination of the random effects, similar to the case of firms from Madrid, we assume that both random effects – i.e. *ressalary* and *firmsize* – are normally distributed.

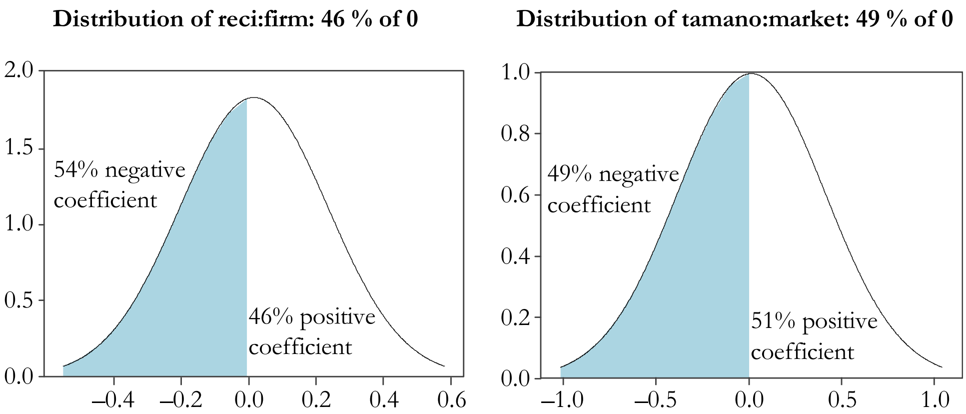
The first random effect, $\hat{\beta}_{ressalary}$, was significant in Models 1 and 3. In Model 1, the estimated distribution is $\hat{\beta}_{ressalary} \sim N(\hat{\mu}_{ressalary} = 0,\ \hat{\sigma}^2{}_{ressalary} = 0.977^2)$ meaning that for approximately 50% of firms, it increases the probability (positive coefficient), whereas it decreases for the rest. In other words, having an average salaried staff implies an equal probability that firms will engage in new-to-market and incremental innovation. In Model 3, the estimated distribution is $\hat{\beta}_{ressalary} \sim N(\hat{\mu}_{ressalary} = -0.067,\quad \hat{\sigma}^2{}_{ressalary} = 0.590^2)$, meaning that, for approximately 46% of the sampled firms, the existence of salaried researchers increases the probability (positive value) of engaging in radical innovation, whereas for 56%, it does not make a vital contribution to product innovation.

Finally, the second random variable, $\hat{\beta}_{firmsize}$, is significant in Models 1 and 3. In Model 1, the estimated distribution is $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize} = 0, \hat{\sigma}^2{}_{firmsize} = 0.380^2)$, meaning that for approximately 50% of firms, the size covariate increases the probability of engaging in radical product innovation (positive value), whereas it decreases for the rest, incentivising them to engage in non-radical-type continuous innovation. In Model 3, the estimated distribution is $\hat{\beta}_{firmsize} \sim N(\hat{\mu}_{firmsize} = 0.012, \quad \hat{\sigma}^2{}_{firmsize} = 0.400^2)$, meaning that for approximately 51% of firms, the probability of engaging in radical innovation with significant novelty in relation to the firm's respective market (positive coefficient) is increased, while for the remaining 49%, it is decreased (firms without any innovative products). Figure 3 displays the distribution of the random effects $\hat{\beta}_{ressalary}$ ~ and $\hat{\beta}_{firmsize}$ in Model 3.

We draw the same conclusion for the Catalonian subsample as the Madrid one. The mixed logit model proved to be superior to the multinomial logit methodology in terms of analysing the profile of innovative enterprises in our regional sample because it helps reveal the real effects of more variables, whether fixed or random. Finally, concerning the significance of the mixed logit model fitted for Catalonia, the p-value of the likelihood ratio test was 0.0006875, meaning that the model was statistically significant. Moreover, the McFadden pseudo R^2 value of 0.1359 indicated an adequate fit.

Figure 3

Distribution of the random effects $\hat{\boldsymbol{\beta}}_{ressalary}$ (left) and $\hat{\boldsymbol{\beta}}_{firmsize}$ (right) for the Catalonian sample in 2016



Note: the random effect comes from Model 3 of Table 12.

Implications and conclusion

This study focused on the profile of Spanish enterprises in relation to three levels of innovation: firms without product innovation and firms that launch products at *newtofirm* or *newtomarket* levels. Two discrete choice models, a multinomial logit model and a mixed logit model, were used to analyse the profile of innovative enterprises operating in high-tech manufacturing sectors and are headquartered in Madrid and Catalonia, the two main economic hubs in Spain. The regional profiles of Spanish enterprises were analysed in relation to firm attributes such as innovation expenditure earmarked for internal and external R&D activities, expenditure dedicated to salaries for researchers, technological development, and firm size.

In the first approach, we assume that all enterprises share homogeneous preferences for each attribute, hence resorting to a multinomial logit model. In Madrid's case, external R&D expenditure was found to affect firms' propensity to engage in radical innovation instead of remaining inert (incremental innovation). In contrast, salaries for researchers proved to be a relevant factor in increasing innovation performance. In this geographically centrally located autonomous community, firms that pay higher salaries to researchers tend to create innovative products instead of resting on their laurels. The mixed logit specification proved to be much more flexible because we identified more variables with explanatory power. For example, internal R&D and technological development measures have become significant. The former finding suggests that more resources increase the probability of less-radical innovation. The latter indicates that firms do not necessarily prefer incremental innovation to no innovation, perhaps because of an administrative attention clash involving ongoing technological investments. Funds for external R&D now lead to different and more nuanced findings, as the possession of the latter is associated with enterprises opting for radical or incremental types of innovation vis-à-vis an inert posture. As far as the random parameters go, our proxy for researchers' salary reflects earlier findings and highlights the prominence of radical innovation rather than incremental innovation. Because the standard deviation of the variable is not significant, it cannot be considered a real random parameter. This is not the case for firm size: the standard deviation is significant in all models, permitting us to compute the proportion of firms in each outcome pair: 83%–17% for radical-incremental innovation (the multinomial delivered here only a similarly positive significant effect); 50%–50% for the 'no' versus 'incremental', and the 'radical' versus 'no' innovation pairs. Thus, treating *firmsize* as a random parameter in the Madrid subsample adds to understanding its role in innovation performance compared with using the multinomial logit method.

In the case of multinomial specification applied to firms headquartered in Catalonia, technological development and firm size are two relevant factors that increase product innovation performance. In this eastern autonomous community, a high ratio of current expenses to technological development is associated with a firm preference for innovative products of any degree of novelty over an inert product innovation posture. In addition, larger enterprises tend to engage in radical innovation compared to 'new to the firm' and 'non-innovation' types. Using the mixed logit model again led to more variables in more models with a statistically significant explanatory power. Funds for external R&D do not necessarily encourage Catalonian firms to opt for incremental innovation (relative to inert product innovation behaviour). The results for technological development are partly similar to those from the multinomial method in how they highlight the choice of firms for radical innovation over none. However, there is also an added emphasis on a revealed preference for radical innovation over incremental innovation. We assumed that Catalonian enterprises display heterogeneous preferences regarding researchers' salaries and firm size as distinguishing attributes. Induced by the former, firms equally choose between radical and incremental innovation postures, and slightly fewer firms opt for radical innovation rather than no innovation (46%-54%). In theory, firm size is similarly depicted in the multinomial specification; we can now precisely specify that larger firms equally prefer radical and incremental innovation outcomes. Further, the size variable is positive and significant for the *newtomarket* and *noinn* pair, similar to the multinomial case. Nevertheless, our calculations reveal that radical innovation is only minimally preferred over non-innovation (a 51%–49% split).

Applying the mixed logit methodology allowed us to compare firms in two prominent Spanish regions. In both subsamples, firms display some sort of inertness in terms of innovation rather than a more creative, innovative approach. Internal R&D funds play no role in Catalonian enterprises in fomenting product innovation, and in Madrid, it only elicits a preference for incremental over radical innovation. External R&D is a much more influential variable for firms headquartered in Madrid than those in Catalonia: former firms use such resources to increase innovative performance. The reverse scenario occurs in the case of expenses dedicated to technological development: there is no role for these expenses in Madrid, while firms in the eastern region use them to buttress radical innovation with beneficial effects on international markets. This is in accordance with prior observations that show the significance of R&D expenses (Anzola-Roman et al. 2018, Barbosa et al. 2013, Bhattacharya–Bloch 2004, Jaumandreu 2009). Salaries dedicated to researchers play a role in both regions; in Madrid, radical innovation over incremental innovation is the unanimous preference, but there is an equal chance of product innovation outcomes in Catalonia. The same pattern is revealed for the radical-no innovation pair: while in Madrid, the former is preferred, in Catalonia, there is a 46%-54% division between the outcomes. Additionally, the results related to the researcher's salaries show that Madrid-based enterprises opt for incremental innovation rather than an inert posture. However, for the Catalonian sample, there is no statistically significant effect. This outcome confirms that wages are positively associated with better innovation performance and productivity, as previously observed (Bester–Petrakis 2003, Lerner–Wulf 2007, Martínez-Ros 2001).

Further, firm size was considered a random variable in both subsamples. Concerning the radical-no innovation outcome, the results are the same for both samples, with equal preferences for both choices. However, Catalonian firms are split regarding the choice between radical and incremental product innovation. Nonetheless, Madrid-based enterprises clearly prefer radical product innovation, spurred by their sheer size. These findings contradict previous research (Laursen–Salter 2006), which indicated the importance of firm size for the incremental type of innovation and the smaller relevance of size for the radical type. An additional difference is that, while there is no significant effect in Catalonia, firm size is not associated with a clear preference for incremental or no product innovation for firms headquartered in Madrid. Overall, our results support the findings of Buesa et al. (2006) and Jaumandreu (2009) that Spanish regions, namely Catalonia and Madrid, differ in their implementation of innovative expenditure and related activities.

Our study contributes to the stream of research on product innovation and the ongoing debate on the effects of firm size and researcher salary on innovation outcomes. The strengths of this study are its examination of the profiles of innovative enterprises through a regional lens and the application of two discrete choice models. A comparison of the results obtained from the two methodological approaches indicates that the mixed logit model facilitates a more thorough assessment of the profile of innovating enterprises in both regions compared with the use of a traditional multinomial logit model. The core feature of the former permits the heterogeneous features of the sampled entities to be revealed, meaning that core variables with fixed and random effects attain significance simultaneously. This agrees with Arbussà–Coenders' (2007) argument that the statistical methodology discussed can generate adequate inferences from complex sample designs.

The analysis built on the mixed logit method was especially capable of highlighting the relevance of examining crucial factors associated with a population of firms in each region that might be associated with greater innovation activity. Such differences are relevant when policymakers fine-tune industrial policies to boost the growth potential of regions. Considering the importance of high-tech manufacturing sectors and the concomitant high value-added production, support for enterprises pursuing innovative activities is needed to promote innovation in advanced manufacturing further. Our results permit us to derive policy implications associated with the prominent variables analysed herein. In our theory-driven research, greater organisational innovation performance is associated with radical innovation, followed by incremental innovation. Interestingly, funds for external R&D are more important for Madrid-headquartered firms than for Catalonian firms, while the reverse holds true in terms of expenses dedicated to technological development. Insofar as such sophisticated industries depend on scientific research, enterprises need to pay attention to increasing the salaries of research staff, perhaps accompanied by the provision of good working conditions and other perks, which economic policy should encourage. Therefore, as found to be relevant in both regions, firms should allocate more funds for such purposes, increasing firm innovativeness. Finally, based on the finding that larger firms are more likely to launch innovative products, the manufacturing industry will benefit from complex industrial policies that target business consolidation, helping enterprises create and market products with greater innovation.

This study was limited by the number of enterprises and variables available in the PITEC dataset. Although this study refers to Spanish enterprises and regions, we believe that a large proportion of the findings have explanatory potential and are transferrable to similar socioeconomic environments. Nevertheless, to create a properly tailored innovation policy for specific regions, the repetition of this study is highly recommended. Future studies on the current topic should ideally incorporate a larger sample of enterprises, more firm attributes, and more regions to enhance the reliability of their conclusions.

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