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REGULAR ARTICLE

Export and variability in the innovative status

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Abstract
The nature of innovation persistence is still open to debate. In this paper, we attempt to shed some light to the topic by providing a novel analysis of the impact of exporting strategies on changes in innovative status. We derive exhaustive information regarding the innovative behavior of firms using a large sample extracted from the Spanish Technological Innovation Panel. Applying both a multinomial and a random-effects probabilistic approach, we observe that exporting experience is relevant to guarantee stability in innovation activities. However, firms exporting only to the EU are comparatively less persistent than those with a broader geographical range, as nearer and safer markets provide less incentives to innovation activities than engaging in broader commercial ventures.

Keywords Innovation · Persistence · Export · Learning

JEL Classification D22 · F14 · L20 · O30

1 Introduction

Existing empirical studies suggest that innovation is a key strategy for increasing productivity and overall firm performance (Expósito & Sanchis-Llopis, 2019; Mohnen & Hall, 2013), increasing a firm's chances of market success. Indirectly, this perspective is supported by Melitz's (2003) seminal work, which identifies a self-selection process in which the most efficient and creative firms are the ones most

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likely to become prosperous exporters. Alternatively, another interpretation considers that the experience accumulated by exporting firms positively affects their innovative capacity and productivity (De Loecker, 2007). Nevertheless, there is still a considerably large gap in the literature concerning the interaction between export dynamics and the likelihood of being a persistent innovator.

Recent literature highlights the relevance of maintaining continuity in innovation activities to differentiate innovative quality and overcome idiosyncratic business cycles (Antonioli & Montresor, 2021). In consequence, the topic is of special interest for policymakers intending to design efficient policies to mitigate current economic backlashes and guarantee steady growth. Furthermore, given the rapid evolution of key aspects of the economy, such as the distribution of labor skills and production relationships, which are driven by technological change (Piva & Vivarelli, 2018), it is important to set out a path for developing a cohesive network of highly innovative firms by determining the characteristics of time-persistent technological progress.

Using an exhaustive database such as the Panel de Innovación Tecnológico (henceforth, PITEC) we focus on the cumulative links between R&D investments, the introduction of innovations, export capacity, and learning processes. More specifically, distinguishing between internal R&D investment and the introduction of product or process innovations, we analyze how a firm's export behavior affects its ability to persist in, or change, its innovation strategies. We are not, however, interested in the traditional approach to persistence. The main novelty of this contribution is the analysis of the determinants that favor variability in innovative status.

To address this, we take two different approaches. First, we classify firms into five categories according to whether they are (i) persistently innovating, (ii) persistently non-innovating, (iii) non-persistently innovating, (iv) firms transitioning once to start innovative activities or (v) firms abandoning once innovative activities. We then determine the stylized facts of each of these groups. Second, we consider only the events of changing from one innovative status to another and estimate the determinants which favor these transitions using a random-effects probit model. Considering the causal and endogenous issues when modeling innovative behavior and export activity (Melitz, 2003; Segarra-Blasco et al., 2022) it is important to remark that our interest lies in the correlations between export activity and innovation variability, and not in the determination of the exact causality between these two dimensions.

Our findings suggest that firms with more consecutive years exporting are more persistent in both R&D and innovation. Simultaneously, this experience discourages abandoning or undertaking innovation activities. Nevertheless, exports themselves do not provide enough incentives for persistence. We observe that firms exporting only to the EU are statistically less persistent than other exporters and experience the same variability as non-exporters. These results have important implications, as new policies should aim at fostering trade possibilities more extensively to guarantee competition and persistent productivity gains from innovation processes.

We consider our contribution relevant to the open debate about the true nature of innovative processes. On the one hand, the evolutionary view (Cohen & Levinthal, 1990; Rosenberg, 1990) considers that the cumulative nature of knowledge—because of persistent R&D investment—favors higher innovative performance and production output. On the other hand, more recent authors (Baber et al., 1991; Gilsing & Nooteboom, 2006; Kor & Mahoney, 2005) argue that innovation success is the result of two synchronized processes: the accumulation of new knowledge and the ability to explore further competitive advantages, which leads to more volatile R&D strategies and innovation outcomes depending on the expected returns, a firm's specific characteristics, and its economic context.

The paper is organized as follows. The next section presents a review of the existing theoretical and empirical foundations of our main topics. Section 3 describes the database and the variables used in the econometric analysis. Section 4 explains the methodological approaches we follow. Afterwards, Sect. 5 presents the empirical results, and the set of robustness checks we applied. Finally, we conclude the research by suggesting policy implications and future lines of research.

2 Literature review

2.1 Innovation persistence from theoretical and empirical perspectives

Since the second half of the twentieth century, certain authors have been developing strong theoretical foundations explaining the motivations that cause companies to persist in their innovative activities. The most prominent of these approaches are the success-breeds-success theory (Flaig & Stadler, 1994; Stoneman, 1983), the sunk costs theory (Sutton, 1991) and the evolutionary theory (Nelson & Winter, 1982). Thanks to them, we know the relevance of knowledge accumulation processes through previous experience, by introducing a diversity of ideas to the test. As well as the path dependence created by past investments, which constrains future behavior.

To calibrate the relevance of these drivers, in terms of both R&D investment and innovation outputs, many empirical studies were conducted in the last few decades. The economics of innovation interprets persistence in diverse ways, for instance, Altuzarra (2017) states the importance of distinguishing between true and spurious state persistence. True state dependence refers to a positive causal relationship between the decision to innovate in one period and the probability of maintaining this activity in the following period. Conversely, spurious state dependence associates the variability in a firm's innovative behavior with the characteristics of its activity, such as firm size, ownership, exports, or public support.[1]

The idea of true state persistence is supported by the publications both of well-established and of more recent authors (Ayllón & Radicic, 2019; Peters, 2009), but there is evidence for the differentiated effect of internal and external characteristics of the firm in the determination of spurious persistence (Ayllón & Radicic, 2019). On one hand, internal factors are mainly related to firm characteristics, such as strategy and

[1] In order to distinguish true from spurious dependence, Altuzarra (2017) estimates a random-effects dynamic type probit model following Wooldridge's (2005) methodology to control for individual heterogeneity and treat the initial conditions problem.

creativeness (Le Bas & Scellato, 2014), as well as firm size, productivity, and financial capabilities (Antonelli et al., 2013; Clausen & Pohjola, 2013). On the other, external factors are defined by the structure of the sector in which the firm operates (Latham & Le Bas, 2006; Matvejeva, 2014), as well as the access to private and public funding, intra-firm or institutional cooperation, and stocks of knowledge (Freitas et al., 2011; Le Bas & Scellato, 2014).

In addition to all this, we know that the degree of innovative persistence differs according to the measure of innovation used, the time frame, and the productive structure under analysis (Cefis, 2003; Cefis & Orsenigo, 2001; Clausen et al., 2012; Geroski et al., 1997; Huang, 2008; Latham & Le Bas, 2006; Malerba et al., 1997; Peters, 2009). Moreover, recent evidence tracing diverse factors related to state and spurious persistence shows how the nature of persistence is strongly determined by past decisions and by a firm's competitive environment (Arroyabe & Schumann, 2022).

2.2 Innovative status, self-selection, and learning-by-exporting

Over the last decade, new literature concerning the dynamics and interrelations between innovation and internationalization decisions has appeared (Becker & Egger, 2013; Casillas et al., 2012; Damijan et al., 2010; Máñez et al., 2015). Consequently, it seems reasonable to interconnect them and treat the effects of international integration as a critical determinant of spurious innovation persistence. Focusing on exports as our preferred internationalization strategy, we must consider two effects with strong theoretical and empirical foundations. On the one hand, contributions such as Melitz (2003) and Bernard et al. (2003) take the seminal evidence proved by Jovanovic (1982) and Hopenhayn (1992) and develop the notion of self-selection. This states that only a restricted proportion of firms—the most productive ones—can internationalize successfully. On the other hand, some authors calibrate how export activities enhance firm performance through the adoption of innovation (De Loecker, 2007). This process of acquisition of knowledge is identified as learning-by-exporting and directly affects the innovative behavior of firms (Alegre et al., 2012; Fernández-Mesa & Alegre, 2015). Furthermore, recent evidence identifies two dimensions of learning-by-exporting, spatial and temporal (Segarra-Blasco et al., 2022).

Although there are few studies aiming to disentangle the association between innovation persistence and international trade, relevant sources do exist. For instance, Andersson and Lööf (2009) show how persistence favors the consistency of learning-by-exporting effects in the acquisition of knowledge. Consequently, Lööf et al. (2015) conclude that exporting and innovation persistence are highly correlated and that each has a positive effect on productivity changes.

2.3 Hypotheses

Based on the reasoning presented in Sect. 2.2, we expect that exporters with greater experience will be more likely to be persistent innovators and, if they did not undertake innovative activities before, more likely to become innovators. This idea is in line with the accumulation of knowledge thanks to exporting experience and competitive needs (De Loecker, 2007). This increases consistency in innovation activities and favors their continuity (Andersson & Lööf, 2009; Lööf et al., 2015). Here, the accumulation of export experience is given by the number of consecutive years in which the firm has been exporting. Therefore, our hypotheses are the following:

H_{1a}: Being an exporter for a greater number of consecutive years increases the likelihood of being a persistent innovator.
H_{1b}: Being a persistent exporter increases the incentives to undertake innovation activities.

However, recent evidence gives us the intuition that, to completely understand the scope of learning-by-exporting effects, we should introduce a spatial dimension of trade to the analysis (Mendoza, 2010; Segarra-Blasco et al., 2022; Tse et al., 2017). Due to the characteristics of our data, we cannot identify spatial learning-by-exporting such as in Segarra-Blasco et al. (2022). We can, nevertheless, proxy this effect by the geographical areas to which firms export, thus:

H_{2a}: Firms with a wider geographical exporting range are more likely to be persistent innovators.
H_{2b}: Companies exporting to more competitive markets are more prone to undertake innovation activities.

3 Data and descriptive statistics

3.1 The database

Spain is a moderate innovator with a large share of non-innovative firms which have the potential to undertake innovation activities (European Commission, 2021; Ministerio de Industria, C. y T., 2020). Thus, we consider it an interesting case for studying the determinants of these types of activities and their persistence.

We use highly detailed firm-level data from PITEC, which contains information collected yearly by the Spanish National Institute of Statistics (INE), supported by the Spanish Foundation for Science and Technology (FECYT). The surveying methodology and the diverse definitions of innovation follow the Oslo Manual (OECD & Eurostat, 1997), ensuring international comparability and allowing the data to serve as input for the Community Innovation Survey.

The firms composing the database are in Spain. The sectors covered are agriculture, industry, construction, and services, according to the NACE-2009 classification. A census is used for the population of firms with more than 200 employees and a stratified sample for those with less than 200 employees.

For conducting our analysis, we applied filters to the original data. First, we decided to cover only the period 2005−2016, as the initial years of the sample have less complete information. Additionally, we consider only firms operating in the manufacturing and service sectors—with at least ten successive observations—. Furthermore, we drop from the sample firms founded before the year 1800, as they

Table 1 Cross-table showing the R&D and innovative status of distribution of firms

R&D status	Innovative status				
	(1)	(2)	(3)	(4)	(5)
(1)	68.78	1.3	9.16	12.6	8.16
(2)	9.38	34.12	19.68	8.62	28.2
(3)	23.78	1.11	30.45	23.13	21.52
(4)	29.63	0.63	19.93	40.77	9.04
(5)	15.33	3.68	21.21	11.35	48.44

All values show relative frequencies. (1) Persistent innovators. (2) Persistent non-innovators. (3) Non-persistent innovators. (4) Firms adopting innovation activities. (5) Firms abandoning innovation activities

are usually not very agile companies and, in many cases, they are cooperatives and companies with moderated innovative and export capacity. As a result, we obtain an unbalanced sample of 62,171 firm-year observations corresponding to 5,176 firms.

PITEC has relevant positive and negative aspects which need clarification before deepening our analysis. It is well known that this data set is a copious source of information regarding firms' innovative behavior. Despite this, it lacks disaggregated information on other characteristics not related to innovation. For instance, we cannot know to how many—or exactly which—foreign markets a specific firm exports. While this limits aspects of our current research, it opens new lines for the future.

3.2 Variables

To develop our empirical methodology, we need to define and classify the innovative behavior of each firm according to its persistence. We thus create two categorical variables, the first identifying firms investing in internal R&D, and the second identifying firms introducing product or process innovations.

Therefore, we know into which of five mutually exclusive categories a firm fits i.e. whether conducts innovation activities in every period of the sample (*Persistent innovator*), in no period (*Persistent non-innovator*), if it changes its innovative status more than once (*non-persistent innovator*), if it changes its position once to start innovating (*Adopting innovation*), or if it changes its status once to stop innovating (*Abandoning innovation*). With the purpose of analyzing status variability, and in line with the literature (Arroyabe & Schumann, 2022), we build a set of dichotomous variables which take a value 1 whenever a firm changes its innovative status in the period $t-2$ and has sustained this change to the period t.

Table 1 cross-tabulates these variables, demonstrating several relevant facts. Most firms persistently investing in internal R&D are, firstly, persistent innovators (68.78%) and, secondly, starting to introduce innovations (12.60%). However, approximately two-thirds of the firms which never invest in internal R&D do not introduce any innovations

(34.12%) or transition to stop introducing them (28.20%), while a significant percentage (19.68%) change status more than once.

For non-persistent investing firms, the distribution among categories is balanced, but they are likely to introduce at least one innovation. Moreover, most firms that start to invest in R&D also start to introduce innovations (40.77%), or persistently introduce them (29.63%). For firms that transition to stopping investing, a sizeable proportion also shift to stopping introducing innovations (48.44%) or to experimenting with diverse changes of status (21.21%).

As determinants, we use variables defining observable firm characteristics which we use as proxies for the effects of entering export dynamics. The first of these is a continuous variable identifying the number of consecutive years that the firm has been exporting. The second is a set of dummies identifying whether a firm does not export, exports only to the EU, exports only outside the EU, or if it has adopted an extensive strategy exporting inside and outside the EU.

Additionally, we include firm characteristics such as its labor productivity—in terms of sales per employee—, size, the proportion of employees with higher education, age, physical investment, public investment, cooperation and whether the firm belongs to a group. We also consider sectorial specific controls. More specifically, we include the technological cluster in which the company operates—High-tech manufactures, low-tech manufactures, knowledge-intensive service sectors or non-knowledge-intensive service sectors—(Añón Higón et al., 2022; Bérubé & Mohnen, 2009; Cassiman & Veugelers, 2002; Coad, 2018; Coad et al., 2016; Leiponen, 2005; Mohnen & Röller, 2005; Piga & Vivarelli, 2003). Tables 2 and 3 describe the main characteristics of these variables.

4 Methodology

To analyze our hypotheses, we undertake two different econometric analysis. First, we analyze the characteristics of each classification of innovator according to the degree of persistence using multinomial modeling. Then, we examine the factors leading to transitioning events in R&D investment and innovation status using a random-effects probit approach.

In the first step, using multinomial analysis, we aim to identify the association between the exogenous variables and our five groups of innovators according to their persistence defined in Sect. 3. Those are persistent non-innovators ($k=0$), persistent innovators ($k=1$), non-persistent innovators ($k=2$), firms transitioning to innovate ($k=3$) and firms transitioning to stop innovating ($k=4$). The ordering of the categories is not relevant. Hence, the probability of belonging to each classification is:

$$\Pr\left(\mathrm{Y_i} = \mathrm{k}\right) = \frac{e^{\beta kXi}}{1 + e^{\beta 1Xi} + e^{\beta 2Xi} + e^{\beta 3Xi} + e^{\beta 4Xi}}, \quad \text{if } \mathrm{k} \in \{1, 2, 3, 4\}$$

$$\Pr\left(\mathrm{Y_i} = 0\right) = \frac{1}{1 + e^{\beta 1Xi} + e^{\beta 2Xi} + e^{\beta 3Xi} + e^{\beta 4Xi}}, \quad \text{if } \mathrm{k} \notin \{1, 2, 3, 4\}$$

Table 2 Definition of the variables

Variables	Type	Definition
Dependent variables		
R&D status	C	Categorical variable identifying persistence in R&D status of firms using "Undertake R&D" and "Stop R&D" binary variables
Innovative status	C	Categorical variable identifying persistence in innovation outcomes using "Undertake innovation" and "Stop innovation" binary variables
Undertake R&D	B	1 if the firm has changed its R&D status from non-investor to investor during the period $t-2$ to t; 0 otherwise
Stop R&D	B	1 if the firm has changed its R&D status from investor to non-investor during the period $t-2$ to t; 0 otherwise
Undertake innovation	B	1 if the firm has changed its innovative status from non-innovator to innovator during the period $t-2$ to t; 0 otherwise
Stop innovation	B	1 if the firm has changed its innovative status from innovator to non-innovator during the period $t-2$ to t; 0 otherwise
Export activity indicators		
Exporting only to the EU	B	Exporting only to the EU
Exporting only outside the EU	B	Exporting only outside the EU
Exporting inside and outside the EU	B	Exporting inside and outside the EU
Non exporter	B	Not exporting
Consecutive years exporting	N	Number of consecutive years exporting
Firms' characteristics		
Sales per employee	N	Sales per employee
Size	N	Firm size measured in number of employees
Human capital	N	Proportion of employees with higher education
Age	N	Firm age
Physical investment	N	Investment in plants, machines, equipment, and ICT as a percentage of the total turnover
Public financing	B	1 if the firm receives public financing during $t-2$ to t; 0 if otherwise
Cooperation	B	1 if the firm cooperates with other agents during $t-2$ to t; 0 otherwise

Table 2 (continued)

Variables	Type	Definition
No group	B	1if the firm does not belong to a group; 0 otherwise
Head	B	1 if the firm is the head of a group; 0 otherwise
Subsidiary	B	1 if the firm is a subsidiary of a group; 0 otherwise
Sector specific controls		
Cluster	B	Dummy variables identifying the technological cluster in which the firm operates (high-tech and low-tech manufactures, KIS and non-KIS sectors)

C refers to categorical variables, B to binary variables and N to numerical variables

Table 3 Description of the variables

Variables	Mean (std. dev.)	N	min	max
Dependent variables				
R&D status				
Persistently investing	0.316 (0.465)	62,112	0	1
Persistently not investing	0.175 (0.380)	62,112	0	1
Diverse change of status	0.132 (0.338)	62,112	0	1
Transitioning to start investing	0.105 (0.306)	62,112	0	1
Transitioning to stop investing	0.272 (0.445)	62,112	0	1
Innovating status				
Persistently innovating	0.338 (0.473)	62,112	0	1
Persistently not innovating	0.076 (0.265)	62,112	0	1
Diverse change of status	0.182 (0.386)	62,112	0	1
Transitioning to start innovating	0.159 (0.366)	62,112	0	1
Transitioning to stop innovating	0.245 (0.430)	62,112	0	1
Undertake R&D	0.024 (0.152)	57,271	0	1
Stop R&D	0.042 (0.200)	57,271	0	1
Undertake innovation	0.035 (0.183)	57,271	0	1
Stop innovation	0.041 (0.197)	57,271	0	1
Export activity indicators				
Exporting status				
Non exporter	0.309 (0.462)	52,211	0	1
Exporting only to the EU	0.116 (0.320)	52,211	0	1
Exporting only outside the EU	0.133 (0.339)	52,211	0	1
Exporting inside and outside the EU	0.442 (0.497)	52,211	0	1
Consecutive years exporting	3.530 (3.598)	52,211	0	12
Firms' characteristics				
Sales per employee (thou. Euros)	273.052 (4,445,950)	57,270	0	1.04e+9
Size	234.541 (941.381)	57,296	0	25,022
Human capital	25.928 (26.218)	52,191	0	100
Age	28.840 (20.224)	62,112	0	181
Physical investment	0.088 (1.351)	57,253	0	185.055
Public financing	0.341 (0.474)	57,271	0	1
Cooperation	0.290 (0.454)	62,112	0	1
Group				
No group	0.583 (0.493)	57,271	0	1
Head	0.085 (0.278)	57,271	0	1
Subsidiary	0.332 (0.471)	57,271	0	1
Sector specific controls				
Technological cluster				
Low-tech manufactures	0.451 (0.498)	62,112	0	1
High-tech manufactures	0.340 (0.474)	62,112	0	1
KIS sectors	0.125 (0.331)	62,112	0	1
Non-KIS sectors	0.084 (0.278)	62,112	0	1

n (Firms) = 5,176

where Pr ($Y_i = k$) identifies if the firm i belongs to the kth category, X_i is a matrix with the exogenous variables and the coefficients β_k measure the relative change to the $Y_i = 0$ classification, β_0 is set to 0 as it is the reference group. The estimated parameters are interpreted as follows:

$$\frac{\Pr(\text{Yi} = k)}{\Pr(\text{Yi} = 0)} = \frac{e^{\beta kXi}}{e^{\beta 0Xi}} = e^{(\beta k - \beta 0)Xi} = e^{\beta k}, \quad \text{if } k \in \{1, 2, 3, 4\}$$

where e^{β} indicates the likelihood of the outcome to fall in the comparison group compared with the probability of falling in the reference category (Greene, 2003).

For the second approach, we focus on the event of transitioning from a particular R&D or innovative status to another. With this purpose, we create dichotomous variables that take value 1 (one) whenever a firm changes its innovative behavior in period $t - 2$ and maintains the new status in period t. We consider that the determinants prompting non-innovative firms to undertake innovative activities are not necessarily the counterfactuals for an innovative firm to become non-innovative. Thus, we differentiate these two evolutions and treat them independently.

Compared to previous methodologies used to analyze innovation persistence from a dynamic perspective (Peters, 2009; Wooldridge, 2005), our objective variables allow us to focus specifically on spurious persistence. This is possible because the notion of status variability bypasses the need of estimating true state persistence, as it is imposed that previous innovation activities have not been continued in the present. This simplifies in a great manner the dynamic framework of the modeling structure, providing more flexibility to the methodology.

Ideally, when operating with panel data, we should account for unobserved heterogeneity by treating α_i as a fixed effect to steer clear from any restrictions on the unobserved effects related to individual heterogeneity (Heckman, 1987). Nevertheless, theory shows that the Fixed Effects estimator provides a bias of order O(T − 1) when using maximum likelihood, which is the case with probabilistic models.

Corrections, such as the ones proposed by Arroyabe and Schumann (2022), might be applied. However, they would limit the amount of information we can include in our regressions, as most of the observations do not comply with the criteria necessary to apply the methodology. Consequently, we select the Random Effects estimator, which allows us to circumvent the bias problem by explicitly modeling the unobserved heterogeneity parameter without losing firm-year observations. Starting from:

$$Y_{it} = 1\left\{\theta X_{it} + c_i + t_i + e_{it} > 0\right\}$$

where X_{it} is a vector of exogenous variables, θ is a vector of parameters, c_i is the constant term for each individual i, t_i introduces a dummy variable for each year of the sample to control for homogenous shocks, and e_{it} is the error term.

Considering the distributional assumptions to be imposed in the error term, we must account for non-linearity:

$$e_{it} \mid X_{it}, c_i, t_i \sim NIID(0, 1)$$

which leads to the final expression:

$$Pr\left(Y_{it}\,\middle|\,X_{it},c_i,t_i\right)=\Phi\left(\theta X_{it}+c_i+t_i\right).$$

We understand that estimating innovative behavior through tools related with firm productivity and export activity may cause endogeneity issues, as innovation increases exports by increasing firm productivity and competitiveness, and, at the same time, export activity fosters innovation via LBE effects. Nevertheless, the interest of this research does not lie on the exact determination of the whole innovation-productivity-export process, we intend to provide some insights on the effect that learning may have on the innovative status of firms.

Regarding the explanatory variables, we applied several modifications to correct potential empirical issues. For instance, we transform all numerical variables to logarithms, to improve the normality of the data distribution (Bellemare & Wichman, 2020). We lag all explanatory variables, to avoid time-specific issues with the introduction of the information to the dataset. And, finally, time-specific dummies are to account for homogeneous shocks across firms, as a control for cross-sectional dependence (Pesaran, 2007).

5 Empirical results

5.1 Multinomial analysis

Tables 4 and 5 report the outcomes of the multinomial logistic regressions for internal R&D investment and the introduction of product and process innovations.

All the parameters refer to the probability of being in the following categories of persistence: (1) persistent investors/innovators, (2) non-persistent investors/innovators, (3) transitioning to start investing/innovating or (4) transitioning to stop investing/innovating compared to the base outcome (0) persistent non-investors/innovators.

There are several distinct effects of export activity between the R&D investment and innovation specifications. On the one hand, Table 4 shows how firms exporting only to the EU are less likely to be persistent investors, but more prone to transition to start investing in R&D. Exporting only outside the EU is strongly associated with firms transitioning to start investing but also increases the likelihood of being a non-persistent investor or a firm transitioning to stop investing. Exporting extensively inside and outside the EU has a positive effect on the probability of being all kinds of investor.

Table 5 shows how exporting only to the EU favors only transitioning events at a 5% significance level. Exporting only outside the EU is associated with the firms transitioning to introduce product or process innovations and exporting extensively favors all innovation persistence and transition events. Regarding the number of consecutive years exporting, we observe a positive association with persistence in all innovation activities, also discouraging all transitioning events. Additionally,

Table 4 Multinomial logit for R&D investors

Variable	(1) Persistent investors	(2) Diverse changes of status	(3) Transitioning to invest	(4) Transitioning to stop investing
Exporting only to the EU	− 0.191*** (0.072)	− 0.054 (0.072)	0.402*** (0.080)	0.044 (0.059)
Exporting only outside the EU	0.110 (0.127)	0.445*** (0.128)	0.668*** (0.142)	0.354*** (0.111)
Exporting inside and outside the EU	0.470*** (0.074)	0.475*** (0.075)	0.934*** (0.083)	0.351*** (0.064)
Consecutive years exporting	0.098*** (0.009)	− 0.005 (0.010)	− 0.030*** (0.010)	0.005 (0.008)
Turnover per employee (Logs)	− 0.092*** (0.022)	0.057** (0.023)	0.071*** (0.026)	0.056*** (0.018)
Size (Logs)	0.138*** (0.016)	− 0.138*** (0.016)	0.025 (0.018)	− 0.243*** (0.013)
Human capital (Logs)	0.443*** (0.015)	0.196*** (0.015)	0.320*** (0.017)	0.195*** (0.012)
Age (Logs)	− 0.158*** (0.032)	− 0.208*** (0.034)	− 0.191*** (0.037)	− 0.240*** (0.029)
Physical investment (Logs)	− 0.048*** (0.009)	− 0.014 (0.009)	− 0.041*** (0.010)	− 0.003 (0.007)
Public financing	1.647*** (0.062)	1.142*** (0.066)	1.446*** (0.067)	0.758*** (0.064)
Cooperation	1.031*** (0.056)	0.575*** (0.059)	0.628*** (0.061)	0.407*** (0.057)
Lead	0.568*** (0.078)	0.438*** (0.082)	0.261*** (0.089)	0.346*** (0.073)
Subsidiary	− 0.230*** (0.046)	− 0.184*** (0.048)	− 0.329*** (0.053)	− 0.113*** (0.041)
High-tech manufactures	0.982*** (0.043)	0.270*** (0.046)	0.384*** (0.050)	0.348*** (0.040)
KIS sectors	1.590*** (0.090)	0.853*** (0.092)	1.333*** (0.097)	0.804*** (0.082)
Non-KIS sectors	− 1.877*** (0.087)	− 1.006*** (0.075)	− 1.032*** (0.091)	− 0.614*** (0.055)
Time dummies	Yes			
Joint significance of time dummies	(0.000)***			
Observations	47,066			
Number of firms	4905			
LR test	0.000***			
Pseudo-R^2	0.196			

Base outcome: persistent non-investors

*p < 0.1; **p < 0.05; ***p < 0.01. All values show coefficient estimates (std. error)

Table 5 Multinomial logit for innovators

Variable	(1) Persistent innovators	(3) Diverse changes of status	(4) Transitioning to innovate	(5) Transitioning to stop innovating
Exporting only to the EU	0.071 (0.095)	0.169* (0.090)	0.395*** (0.097)	0.173** (0.085)
Exporting only outside the EU	− 0.034 (0.158)	0.046 (0.152)	0.355** (0.160)	− 0.078 (0.146)
Exporting inside and outside the EU	0.297*** (0.099)	0.174* (0.095)	0.619*** (0.100)	0.298*** (0.090)
Consecutive years exporting	0.044*** (0.013)	− 0.016 (0.012)	− 0.050*** (0.013)	− 0.006 (0.012)
R&D investment	0.481*** (0.118)	− 0.672*** (0.119)	− 0.195 (0.120)	− 0.741*** (0.119)
Turnover per employee (Logs)	0.263*** (0.028)	0.195*** (0.027)	0.182*** (0.029)	0.140*** (0.025)
Size (Logs)	0.167*** (0.019)	− 0.072*** (0.018)	0.069*** (0.020)	− 0.158*** (0.017)
Human capital (Logs)	0.201*** (0.019)	0.139*** (0.017)	0.156*** (0.020)	0.158*** (0.016)
Age (Logs)	− 0.093** (0.045)	− 0.277*** (0.044)	− 0.150*** (0.047)	0.070* (0.042)
Physical investment (Logs)	− 0.028** (0.011)	− 0.004 (0.011)	− 0.024** (0.012)	0.009 (0.010)
Public financing	− 0.146 (0.103)	− 0.182* (0.105)	− 0.244** (0.105)	− 0.191* (0.105)
Cooperation	0.877*** (0.123)	0.286** (0.125)	0.601*** (0.125)	0.315** (0.126)
Lead	0.359*** (0.111)	0.394*** (0.111)	0.384*** (0.114)	0.254** (0.107)
Subsidiary	− 0.019 (0.062)	0.155** (0.060)	0.048 (0.064)	0.024 (0.058)
High-tech manufactures	0.250*** (0.062)	− 0.018 (0.061)	0.148** (0.064)	0.038 (0.058)
KIS sectors	− 0.281*** (0.100)	− 0.169* (0.097)	0.022 (0.102)	− 0.121 (0.093)
Non-KIS sectors	− 0.731*** (0.093)	− 0.553*** (0.079)	− 0.361*** (0.090)	− 0.550*** (0.073)
Time dummies	Yes			
Joint significance of time dummies	(0.000)***			
Observations	47,066			
Number of firms	4905			
LR test	0.000***			
Pseudo R^2	0.177			

Base outcome: persistent non-innovators

*p < 0.1; **p < 0.05; ***p < 0.01. All values show coefficient estimates (std. error)

conducting previous R&D investment increases the likelihood that a firm persistently introduces innovations and discourages non-persistence and transitions.

The effect of labor productivity is noticeably different between R&D and innovation persistence. While more productive firms are not persistent investors of R&D, they are persistent innovators. Firm size and the share of employees with higher education increase the likelihood of being all kinds of innovators except non-persistent investors or innovators.

Concerning firm age, older firms are more likely to be persistent non-investors of R&D and persistent non-innovators. The volume of physical investment negatively impacts the probability of persistently conducting innovation activities or starting them. Finally, receiving public financing favors all kinds of R&D investors, especially persistent and transitioning; however, it is not associated with the introduction of innovations.

The effect of cooperation on R&D and in the introduction of innovation is highly positive and significant. Belonging to a group has diverse effects depending on the role of the firm. On the one hand, leaders are more likely to be present in all kinds of profiles in all innovation activities. On the other hand, subsidiaries are not likely to develop R&D, but they seem to be non-persistent innovators.

The outcomes obtained for each technological cluster are also highly consistent. High-tech manufacturers tend to be persistent R&D investors and innovators, compared to low-tech manufacturers, as well as more active innovators in general. The same pattern occurs for firms belonging to KIS sectors. Firms belonging to non-KIS sectors tend to be less active and persistent in terms of innovative activities.

5.2 Analysis of status changes

Tables 6 and 7 report the estimation results for internal R&D [columns (1) and (2)] and introduction of product or process innovations [columns (3) and (4)] on innovative state variability. Table 6 provides information about changes between investing/innovating to stop conducting these activities. For this purpose, we only consider firms with at least two consecutive years reporting innovation activities. To acquire a general definition of the determinants that favor changes of states, we do not discriminate between the different persistence groups (Sect. 3) in the regression. We introduce group discrimination in the robustness checks presented in Sect. 5.3.

Table 7 provides information about the transitions between not conducting innovative activities to start conducting them. We consider firms reporting at least two consecutive periods without R&D investment and product or process innovation. Again, we separate the spatial dimension of exports from the temporal one for minimizing the issues related to high correlations between explanatory variables.[2] We observe how firms exporting only outside the EU and extensive exporters are less likely to stop innovation activities, this effect is more substantial for R&D

[2] This consideration was not necessary for the multinomial analysis as the estimation methodology allows for more flexibility regarding these issues.

Table 6 Random effects probit for stopping innovation activities

Variable	R&D investment		Innovation	
	(1)	(2)	(3)	(4)
Exporting only to the EU		– 0.040 (0.039)		0.022 (0.040)
Exporting only outside the EU		– 0.187*** (0.039)		– 0.091** (0.045)
Exporting inside and outside the EU		– 0.135*** (0.030)		– 0.033 (0.032)
Consecutive years exporting	– 0.025*** (0.004)		– 0.007* (0.004)	
Sales per employee (Logs)	0.025* (0.014)	0.016 (0.013)	0.007 (0.015)	– 0.001 (0.014)
Size (Logs)	– 0.128*** (0.010)	– 0.134*** (0.009)	– 0.083*** (0.010)	– 0.088*** (0.010)
Human capital (Logs)	– 0.085*** (0.009)	– 0.105*** (0.008)	0.017* (0.010)	0.011 (0.009)
Age (Logs)	– 0.004 (0.020)	– 0.011 (0.018)	– 0.005 (0.022)	– 0.024 (0.020)
Physical investment (Logs)	0.033*** (0.005)	0.035*** (0.005)	0.011* (0.006)	0.009* (0.005)
Public financing	– 0.417*** (0.028)	– 0.422*** (0.026)	– 0.020 (0.033)	– 0.030 (0.031)
Cooperation	– 0.205*** (0.028)	– 0.212*** (0.026)	– 0.274*** (0.036)	– 0.297*** (0.033)
Lead	0.025 (0.046)	0.034 (0.044)	– 0.013 (0.051)	0.005 (0.048)
Subsidiary	0.103*** (0.029)	0.099*** (0.027)	0.045 (0.031)	0.043 (0.029)
High-tech manufactures	– 0.156*** (0.026)	– 0.162*** (0.025)	– 0.008 (0.029)	– 0.016 (0.027)
KIS sectors	– 0.068 (0.044)	– 0.070* (0.040)	0.144*** (0.045)	0.118*** (0.042)
Non-KIS sectors	0.313*** (0.050)	0.323*** (0.046)	– 0.045 (0.050)	– 0.004 (0.046)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.001)***	(0.000)***	(0.000)***	(0.000)***
Observations	34,863	38,587	38,625	43,010
Number of firms	4274	4291	4780	4797
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	– 7062.212	– 8161.390	– 6376.275	−7182.337

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. All values show coefficient estimates (std. error)

Table 7 Random effects probit for starting innovation activities

Variable	R&D investment		Innovation	
	(1)	(2)	(3)	(4)
Exporting only to the EU		− 0.056 (0.050)		− 0.045 (0.044)
Exporting only outside the EU		0.106** (0.049)		− 0.070 (0.043)
Exporting inside and outside the EU		0.042 (0.039)		− 0.103*** (0.035)
Consecutive years exporting	− 0.021*** (0.005)		− 0.023*** (0.005)	
Sales per employee (Logs)	− 0.011 (0.019)	− 0.012 (0.018)	− 0.003 (0.016)	− 0.006 (0.015)
Size (Logs)	0.013 (0.013)	0.008 (0.012)	− 0.014 (0.011)	− 0.016 (0.010)
Human capital (Logs)	0.034*** (0.012)	0.038*** (0.012)	− 0.019* (0.011)	− 0.018* (0.010)
Age (Logs)	− 0.013 (0.025)	− 0.010 (0.023)	− 0.068*** (0.023)	− 0.066*** (0.020)
Physical investment (Logs)	− 0.021*** (0.007)	− 0.017*** (0.006)	− 0.047*** (0.006)	− 0.045*** (0.006)
Public financing	0.283*** (0.031)	0.270*** (0.029)	0.026 (0.029)	0.028 (0.027)
Cooperation	0.073** (0.032)	0.061** (0.030)	0.026 (0.030)	0.026 (0.028)
Lead	0.099* (0.057)	0.078 (0.054)	0.037 (0.052)	0.052 (0.049)
Subsidiary	0.013 (0.037)	0.012 (0.035)	0.029 (0.033)	0.020 (0.031)
High-tech manufactures	0.028 (0.033)	0.019 (0.032)	− 0.025 (0.030)	− 0.027 (0.029)
KIS sectors	0.115** (0.054)	0.138*** (0.050)	− 0.031 (0.049)	0.001 (0.044)
Non-KIS sectors	− 0.274*** (0.068)	− 0.164*** (0.063)	0.068 (0.057)	0.084 (0.052)
Time dummies	Yes	Yes	Yes	Yes
Joint significance of time dummies	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Observations	19,252	22,114	18,417	21,168
Number of firms	3139	3291	3084	3235
Wald test for zero slopes	0.000***	0.000***	0.000***	0.000***
Log likelihood	− 4462.551	− 4961.392	− 5593.563	− 6455.144

*p < 0.1; **p < 0.05; ***p < 0.01. All values show coefficient estimates (std. error)

investment. Each consecutive year of exporting also decreases the probability of changing innovate status. Again, this effect is stronger when considering R&D.

Regarding firm size, firms with more employees are less likely to stop innovation activities. The volume of human capital also decreases the likelihood of abandoning R&D investment, at the same time it fosters firms which did not devote resources to R&D to start doing so. The effects of physical and public investment are opposites, they discourage and encourage, respectively, persistence in innovation activities.

Firms that are cooperating are also less likely to abandon all innovation activities and more likely to undertake R&D investment. There are not significant effects associated with group leaders, but subsidiaries seem more likely to abandon R&D investment.

Regarding the technological cluster, high-tech manufacturers are less likely to abandon R&D activities compared to low-tech manufacturers. Over and above that, firms operating in KIS and non-KIS are more prone to abandon innovation activities. However, KIS are more likely to undertake R&D activities.

5.3 Further results and robustness checks

In this section, we address potential issues related to the robustness of our results. Firstly, with the intention of reducing the outcome volumes, our main results contain firms belonging to the manufacturing and service sectors. Our assumption was that the real values of the other parameters are not statistically related to the sector of activity. It is, however, necessary to check whether this assumption is true.

We manage this issue by defining the determinants of persistent R&D investors by each technological cluster (see Table S1 in supplementary material). We find that our main variables of analysis, related with firms' export activity, do not show major differences from our previous results. Firms with more experience in international trade are more likely to be investing persistently, however there is a significant loss of significance in the geographical dimension of LBE. Still, we observe that being an exporter only to the EU is not a determinant associated with persistent firms in high-tech manufacturing and that for low-tech manufactures exporting inside and outside the EU is especially relevant. In addition to sectorial disaggregation, we also increase the restrictions in the Random Effects probabilistic analysis of the changes in innovative status to assess the consistency of our estimated outcomes. On the one hand, for changes from investing/innovating to stopping conducting these activities, we consider only persistent innovators and firms transitioning to stop investing/innovating (see Table S2 in supplementary material). On the other hand, for changes from not investing/innovating to start these activities we consider only persistent non-innovators and firms transitioning to invest/innovate (see Table S3 in supplementary material).

The robustness check in Table S2 (supplementary material) does not show significant differences compared to our main results, as all the effects maintain their sign and impact on the probability of changing from one status to the other. The robustness check in Table S3 (supplementary material) does not show significant changes regarding R&D outcomes, but certain parameters are less significant in the introduction of product and process innovation specification, for example, the number of consecutive years exporting.

6 Discussion and conclusion

The aim of this research is to explore the association between the effects of the diverse dimensions of learning-by-exporting and innovative status variability at firm level using the Spanish CIS for the period 2005−2016. By innovation activities we refer to internal R&D investment and the introduction of product or process innovations and we disentangle whether export activity favors persistence in innovation activities or status transitions among them.

At the empirical level, we determine the nature of this interconnection by using two approaches. First, we apply a multinomial perspective to model the stylized determinants of persistent innovators, persistent non-innovators, non-persistent innovators, firms adopting innovation and firms abandoning innovation. Second, we analyze the nature of internal R&D and innovative status changes applying a Random Effects probabilistic approach.

Our results show significant differences in the level of persistence between exporting and non-exporting firms, confirming earlier evidence (e.g., Andersson & Lööf, 2009; Lööf et al., 2015). However, the main novelty of our research arises from the distinction between the time and spatial dimensions of learning-by-exporting. We find that firms with more experience in international trade and the ones conducting previous R&D activities tend to be more persistent in all innovation activities, confirming our hypothesis H_{1a}. Simultaneously, this time dimension reduces the incentives to undertake or stop these activities and suggests that firms already established in foreign markets but not innovating have less incentives to change their R&D or innovative status. This result runs counter to our hypothesis H_{1b}.

Other outcomes expose how not all exporters are more persistent per se. Firms exporting only to the EU are comparatively less innovatively persistent than those with a broader geographical range. This is strengthened when we observe the probabilistic analysis of the changes of status, there are non-significant differences among non-exporters and firms exporting only to the EU, only firms exporting outside the EU or to both markets are less likely to stop innovation activities. Nevertheless, when considering the event of undertaking R&D or innovation, the effects of the spatial dimension are less clear. Analyzing these results, we can confirm the hypothesis H_{2a}, and depending on the econometric specification also the hypothesis H_{2b}.

From an empirical point of view, our research highlights that persistence in innovation activities and exporting are two closely interconnected dimensions. Currently, countries like Spain, at a distance from the EU's technological frontier, must pursue an ambitious industrial policy that simultaneously promotes two crucial factors of business competition: presence in foreign markets and innovation. Therefore, policymakers should encourage firms to start broader trade endeavors, with the objective of fostering competitiveness and creating incentives to innovate over a sustained span of time.

Finally, future lines of research may investigate some aspects which we could not address here or overcome some of the limitations of the analysis. For instance, a methodological approach analyzing the dynamics of the whole innovation-productivity-export process is necessary to consolidate the outcomes presented. In addition, expanding the geographical dimension of the learning-by-exporting effects by being able to identify exactly to which countries the firm is exporting is necessary to complete the intention of this paper. This sets the basis for further work exploring the consequences of persistence on the quality of the research developed and innovation outcomes.

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Data availability The data supporting the findings of this study was obtained from the Spanish National Institute of Statistics (INE), and used under license. The public availability of this data could compromise the privacy of the research participants. It can be requested to the corresponding author with the permission of the Spanish National Institute of Statistics (INE).

Declarations

Conflict of interest All authors certify that they have no affiliations with, or involvement in, any organization or entity with financial or non-financial interests in the subject matter or materials discussed in this manuscript.

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