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Comparing Persistence of Product and Process Innovation: A Discrete-Time Duration Analysis of Innovation Spells

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Abstract
The main purpose of this paper is to analyze the influence of previous experience and learning capabilities on survival in product and process innovation for Spanish manufacturing firms in the period 1990–2010. The authors find past and path dependence and confirm the important effect of R&D effort in both types of innovation. Nevertheless, for product innovation, the level of appropriability and the fact of operating in a high-tech sector are crucial for persistence in comparison with process innovation.

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Keywords Persistence in innovation; product innovation; process innovation; discrete-time duration models; panel-data

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1. Introduction.

The phenomenon called "persistence of innovation" is an important topic in the literature on innovation (Antonelli et al., 2012a). The persistence of innovative behavior is identified if a firm which innovates once has a higher probability of innovating again in subsequent periods. Thus, a firm's past experience in innovation has a positive effect on current innovation.

There are plenty of empirical studies on measuring the degree of persistence in innovation using the number of patents, the R&D effort or innovation output indicators as proxy variables (Flaig and Stadler, 1994; Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001; Cefis, 2003; Rogers, 2004; Duguet and Manjon, 2004; Cabagnols, 2006; Mañez-Castillejo et al. 2009; Peters, 2009; Raymond et al. 2010; Triguero and Córcoles, 2013). But, as far as we know, only a few studies measure the degree of persistence in innovation considering innovative spells, i.e., periods of time during which the firm innovates year after year without gaps in its activity (Geroski et al., 1997; Le Bas et al., 2003; Cabagnols, 2003; Jang and Chen, 2011). Therefore, the objective of this paper is to study the persistence of innovative activity by type of innovation. Although the duration analysis has been used in prior work to distinguish between persistent and occasional innovators, our purpose is to determine survival in innovation activities using discrete-time duration models. This methodology enables us to solve the main limitations of continuous-time duration models typically used in the existing literature (unobserved heterogeneity and the proportional hazard assumption).

The literature about persistence in innovation has also identified differentiated patterns when different types of innovation activities (new products, processes, organization methods) are considered. However, the differences between the degree of persistence of process and product innovations are not at all present in the former literature. Most of the studies recognize that there is a degree of association or complementarity between product and process innovation (Reichstein and Salter 2006). Nevertheless, only a few studies pay attention to different patterns of persistence across both types of innovation. Some related literature indicates that product innovation is more persistent than process innovation (Martínez-Ros and Labeaga, 2009; Antonelli et al., 2012a). However, the understanding of the different drivers of persistence in product and process innovation remains limited. In this regard, a more thorough consideration of this topic should be considered. As far as we know, Clausen et al. (2011) is the only study that distinguishes among different sources of persistence in both types of innovation. The availability of a panel-data of more than 20 years and the use of a discrete-time duration model allow us to accomplish this task and to make the distinction between the degree of persistence in product and process innovation. Building upon the dynamic capabilities framework, we present a model that examines the role of learning capabilities in innovation persistence. In this regard, we argue that the ability to be constant in R&D activities, appropriability conditions, technological opportunities and previous episodes of innovation are crucial to current innovative behavior. Nevertheless, these learning capabilities may affect persistence differently considering both types of innovation activities. Hence, the main purpose of our research is to test whether previous experience and learning capabilities have a different influence on persistence in product and process innovation.

This paper contributes to previous literature in several ways. First, we use an empirical methodology that solves some of the problems of prior work based on duration analysis to measure persistence in innovative activity. We model persistent innovative activity by the number of successive years in which a firm innovates (innovation spells) instead of investigating whether firms that innovate in time t~~,~~ innovate in time t+1. For this purpose, we use discrete-time duration models to measure the degree of persistence in innovation. Secondly, we explicitly distinguish between the differences among process and product innovations related to the phenomenon of innovative persistence. To do that, interactions are used in the estimated models. Hence, differentiated patterns of persistence depending on previous experience in each type of innovation are identified. Finally, we jointly measure past and path dependence in product and process innovations. For this purpose, the duration of the previous innovation spell (past dependence) and the number of previous innovation spells (path dependence) are considered.

The remainder of the paper is organized as follows. Section 2 reviews the empirical literature about persistence in innovation and proposes the hypothesis. Section 3 presents the econometric methodology. In Section 4, the data and the variables used are explained. Section 5 summarizes the results. Finally, Section 6 concludes.

2. Literature review and theoretical framework. The determinants of persistence

The volume of literature about persistence in innovation is growing, but it is focused mainly on explaining the probability of doing R&D or innovation without distinguishing different types of innovation. As far as we know, only a few related studies recognize the potential dissimilarities among the degree of persistence of process and product innovations.

Given the complexity of innovation process, firms have to design their innovation strategy and choose between product innovations, process innovations or both. Although most of the studies recognized that there is complementarity between product and process innovation (Reichstein and Salter 2006), a different pattern of persistence should be considered. Some empirical literature indicates that product innovation is more persistent than process innovation (Martínez-Ros and Labeaga, 2009; Antonelli et al., 2012a); persistence is found for product but not for process innovation (Parisi et al. 2006), or its scale and significance differ between both of them (Clausen et al., 2011). In this regard, the diversity of innovative strategies must be considered.

According to Antonelli et al. (2012b), two quite different explanations for innovation persistence can be noted. The first one links innovation persistence with a phenomenon where the probability of introducing an innovation at time “t” is indeed influenced by the introduction of an innovation at time “t-1”. This definition tries to measure the observed persistence attributable to the fact of innovating in the past and not to other firm-specific factors (past dependence). The second one is closely related to the resource-based theory of the firm and dynamic capabilities, where innovation persistence is linked with the internal characteristics and learning capabilities of firms (including previous innovation behavior) and the changing context in which they are localized (path dependence).

Both theoretical explanations are going to be considered in this work. On the one hand, path dependence provides a framework for modeling the effects of historic time on the behavior of agents which are able at each point in time to modify their evolution (Antonelli, 1997). On the other hand, past dependence allows us to identify persistence depending on previous behavior (Antonelli et al., 2012a).

Martínez-Ros and Labeaga (2009) confirm that persistence in process innovation is more affected by the business cycle than persistence in product innovation in a sample of Spanish manufacturing firms from the period 1990-1999. In the same sense, Antonelli et al. (2012a) found that process innovations are characterized by lower levels of long-term stability than product innovations. They argued that the distinction between past dependent and path dependent process is important for explaining the differences between persistence in product and process innovations ~~on~~ in a sample of 451 Italian manufacturing companies during the years 1998-2006. The authors conclude that innovation, especially product innovation, is not only past dependent, as many studies confirm, but also path dependent. Therefore, it is very important to take into account both characters to analyze the patterns of persistence between product and process innovation. According to these results, we formulate the following hypotheses:

Hypothesis 1 (H1): Persistence in product and process innovation are past dependent.

Hypothesis 1a (H1a): Persistence in product innovation is more likely to be path dependent than process innovation.

Path-dependence depends not only on previous innovative episodes, but also on firm-dynamic capabilities. Indeed, learning capabilities are crucial in generating innovations. The resource-based view (RBV) of the firm provides a framework–for exploring the influence of these learning capabilities in innovation persistence. In this work, we assume that firms accumulate knowledge as a strategic asset through R&D and appropriation of returns of innovation (patents).

On one hand, R&D has proven to be a stronger predictor of persistence in innovation in previous empirical studies. Several R&D indicators enable us to explain current innovation output by past innovation input (Raymond et al., 2010). In this regard, a positive relationship has been found between persistence in innovation and lagged R&D (Lelarge, 2006; Triguero and Córcoles, 2013). However, innovation input and innovative output could not be correlated because “R&D reflects only the resources devoted to producing innovative output, but not the innovative activity actually realized” (Audretsch, 2003, p. 18). From our point of view, it is also very important to know whether a continuous effort in R&D (measured in terms of cumulative R&D at the firm level) fosters persistence in innovation. Continuous R&D performers should increase the probability of successful innovation because of high knowledge accumulation. This explanation is based on two arguments. First, knowledge accumulation enhances the probability of future innovation- , the so- called “success breeds success” principle (Flaig and Stadler, 1994; Geroski et al., 1997). Second, the “learning by doing” effect must be taken into account in the persistence of innovative activities (Peters, 2009).

Hypothesis 2 (H2): A continuous effort in R&D increases persistence in product and process innovations.

Hypothesis 2a (H2a): A continuous effort in R&D is more important for persistence in product innovations than for persistence in process innovations.

Another important factor that should be considered is the appropriability of innovation results. The evidence suggests that appropriability is one of the factors shaping the probability to innovate. In this regard, a minimum degree of appropriability is necessary to motivate innovation (Dosi et al., 2006). Although the individual effect of appropriability on persistence has not often been considered in the literature, the degree to which a firm can protect its innovative capabilities from its competitors through patents, trade secrets or utility models must be considered (Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001). Thus, the appropriability regime positively affects the degree of persistence in innovation, but we expect a different effect on the degree of persistence of product and process innovations. Although we know that appropriability conditions differ among industries and technologies, we hypothesize that:

Hypothesis 3 (H3): The level of appropriability pays off in terms of higher persistence in product and process innovations.

Hypothesis 3a (H3a): The level of appropriability enhances persistence in product innovation to a higher extent than persistence in process innovation.

Finally, differences in innovation might be attributed to industry heterogeneity (Peters, 2009). Sectors differ in their R&D and innovative intensity (Dosi, 1988). In this regard, the role of technological opportunities is considered. Technological opportunities assess ease of innovation in a particular sector, taking into account R&D differences by industry (Cohen and Levinthal, 1989). These approaches are mainly associated with the opportunity for radical innovations under specific industry-level conditions. In this regard, firms operating in high-tech industries must be more likely to be persistent in innovation because of their proximity to the technological frontier (Lelarge, 2006; Raymond et al. 2010; Huang and Yang, 2010). According to Clausen et al. (2011), the dynamics of product and process innovation differ depending on the industry in which the firm operates. In this regard, product innovation is more frequent in high-tech firms, while the strategy of process innovation is more usual in low-tech firms. Since we also need to take into account technological opportunities to explain the different determinants of persistence in both types of innovation, we assume that:

Hypothesis 4 (H4): Technological opportunities are expected to play a significant role in process and product innovation persistence.

Hypothesis 4a (H4a): Persistence in product innovation is higher for firms operating in high-tech industries.

3. Methodology.

Following Geroski *et al*. (1997), we define the degree of innovation persistence through the definition of spells. In other words, persistence is measured by the number of consecutive years during which the firm has an innovative output. The main aim of empirical studies of duration data is to analyse the exit probability of the spell in the year "t" conditioned by having remained in this spell at least "T" years. This conditional probability is called the "hazard rate" --the "hazard" function in continuous terms. Formally, the hazard rate is defined as the probability of a firm's ceasing to be an innovator at moment "t" conditioned to have been innovative before "t". Thus, a negative dependency between "t" and the hazard rate indicates a situation of survival of innovation (persistence). By defining "n_i" as the number of innovative firms in period "t" (both complete and censured observations are included) and "h_i" as the number of firms stopping innovation exactly at "t", the hazard rate is calculated in the following way:

$$\emptyset(t) = \Pr(T = t | T \geq t) = \frac{\Pr(T = t)}{\Pr(T \geq t)} = \frac{h_1}{n_1} \qquad (1)$$

From expression (1), the survival function as the complementary distribution function of the hazard rate is defined as:

$$S(t) = \prod_{t(i) \leq t} 1 - \emptyset(t) = \prod_{t(i) \leq t} \left(1 - \frac{h_i}{n_i}\right) \qquad (2)$$

where S(t) is the probability of remaining in the current spell given a period of time "t".

The higher the value of the survival probability, the larger the persistence of the innovation. If we have a sample of spells of different durations (different "T"), the hazard and survival functions can be calculated using the non-parametrical approach proposed by Kaplan-Meier (1958). Note that this method controls for the right-censoring problem but not for the left-censoring problem. Given the random sample of innovative manufacturing firms, the number of consecutive years of innovation for each one is calculated (see Kiefer, 1988)[1]. Since it is possible to interrupt and restart innovation for several times, firms can have multiple spells. The more times the innovation is interrupted and restored, the greater the number of spells and the lower their average duration.

From a dynamic point of view, duration models quantify the influence of different variables on the likelihood of persistence in a specific event (Van der Berg, 2001). Therefore, this empirical methodology is especially suitable for the purpose of this paper.

Previous literature has used both methodologies to analyse the persistence of innovation: continuous models (Cabagnols, 2003; Geroski et. al., 1997; Le Bas et. al., 2003 and Jang and Chen, 2011) and discrete-time duration models (Triguero et. al., 2014). Nevertheless, continuous time models suffer some efficiency drawbacks because of difficulties with ties in the dependent variable, lack of control for unobserved heterogeneity and the assumption of proportional hazards (Brenton et al., 2010; Fugazza and Molina, 2011). Discrete-time models allow us to solve these problems (Hess and Persson, 2011). Thus, taking into account these advantages, we estimate a discrete-time

[1] Therefore, the length of the spells could vary between 1, when the innovative activity is interrupted in the first year, and 21, when firms innovate in the whole period from 1990-2010.

duration model based on a random-effects[2] complementary log-log (clog-log) model. Clog-log determines a more flexible functional form than the probit model (Heckman and Singer, 1984).

Note that duration models do not measure the unconditional probability of a given spell duration (e.g., the probability of maintaining an innovation exactly five years) but is able to estimate the conditional probability (e.g., the likelihood of ceasing innovation in the sixth year conditioned to persistence during the previous five years) (Kiefer, 1988). This conditional probability is the dependent variable and it is known as the "hazard rate" (see equation 1). The general model specification for the random- effect model is:

$$\phi(t) = \beta_1 t.in_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} + \varepsilon_i + \mu_{it} \qquad (3)$$

where '*t.in*' is a variable that identifies the type of innovation of the current spell (product or process); $X1_{it} = (x1_{1it}, x1_{2it}, \ldots, x1_{nit})$ is a vector that includes the state dependence variables: the previous spell duration and the number of previous spells; $X2_{it} = (x2_{1it}, x2_{2it}, \ldots, x2_{nit})$ is a vector of explanatory variables considered: *R&D* activities, having (or not having) patents, technological degree, years in the current spell and other control variables such as size, industrial sector and current year; $"\beta = (" \beta_1 1, \beta_1 2, \beta_1 3, \ldots, \beta_1 n)$ is the vector of associated coefficients; ε_i is the error term that controls for time-invariant fixed effects from a random sample and μ_{it} is the independent error term (mean zero and constant variance).

Equation 3 does not provide possible differences in the effect on persistence of X_1 and X_2 by types of innovation. To do this, it is necessary to implement an alternative specification with interaction coefficients (Buis, 2010).

Starting from equation (3), '*t.in*' is the interacted variable and the general model would be:

$$\phi(t) = \beta_1 t.in_{it} + \beta_2 X1_{it} + \beta_3 X2_{it} + \beta_4 (t.in_{it} * X1_{it}) + \beta_5 (t.in_{it} * X2_{it}) + \varepsilon_i + \mu_{it} \qquad (4)$$

[2] Previous econometric literature provides evidence about estimation problems in discrete-choice models with fixed effects (the incidental parameters problem). Coefficients could be severely biased with small T-periods and a high number of individuals (Nickell, 1981; Greene, 2004 and Fernández-Val, 2009). This fact is particularly relevant in our data sample.

Interaction terms let us isolate the effect of the explanatory variables on the persistence of innovation ($\beta_1, \beta_2, \beta_3$ coefficients), controlling for possible distortions due to significant differences by type of innovation (β_4, β_5 coefficients). For example, it is possible to determine R&D impact on the persistence of total innovation, considering and at the same time quantifying the possible existence of relevant differences in the R&D effect on the persistence of product and process innovation. These results could not be obtained with two separate models for product and process innovation.

4. Data and variables

4.1 Data

To accomplish our research objectives, we use firm-level data for the period 1990-2010 from the Survey of Business Strategies (ESEE, *Encuesta sobre Estrategias Empresariales*) compiled by the Spanish Ministry of Science and Technology. ESEE is, by definition, an unbalanced panel containing an average sample of around 1,800-2,000 firms surveyed yearly for all the industrial sectors that are consistently most representative of the Spanish manufacturing sector. The coverage of the data set is mixed: a random sample for small companies (with fewer than 200 employees) and a complete sample for large firms (with more than 200 employees).

The ESEE data set allows us to construct innovative spells by considering all types of innovation as well as separately taking into account process and product innovations. In addition, it also allows us to identify other influencing factors at the firm-level.

4.2 Variables

Dependent variable

For each firm, we construct our dependent variable on the basis of the yes/no question about the introduction by the firm of new products and processes in a specific year. We identify whether an innovation is introduced in a given year and how long innovative activity is continued without interruption.

Our interest is focused on the length of time a firm is continuously innovating. Therefore, we calculate the discrete exit probability of an innovation spell, in other words, the hazard rates of the current innovative spell (see Table in the Annex 1). Spells are built considering product and process innovation separately. When firms ~~reports~~ product and process innovation simultaneously, they will be registered twice in a given year. This situation does not give rise to econometric problems because in survival models, the reference unit of the panel data is the spell instead of the firm and the time unit is the duration of current spell instead of the current year.

State-dependent variables

Following the theoretical background, we measure previous experience in innovation through the duration of the previous spell and the number of previous spells. Both variables enable us to measure the effect of innovative experience on the current stability of innovation (Joyce, 2005; Shao et al., 2012) and to distinguish between past and path dependence. On the one hand, past dependence --proxied by the duration of the previous spell-- captures the impact of past innovative persistence on present stability (Fougère et. al, 2000). On the other hand, path dependence --proxied by the number of previous innovative spells-- measures the influence of previous episodes of innovation regardless of their duration (Doiron and Gørgens, 2008). Thus, we expect a positive relationship between the duration of the previous spell and persistence and a negative one between the number of previous spells and persistence[3].

Explanatory variables

The existence of sunk costs and learning by doing effects associated with R&D spending justifies the inclusion of the persistence degree in R&D activities. Technological capabilities in the present are the basis for future innovations and their existence encourages the firm to adopt a persistent innovation strategy. We introduce a categorical variable considering all R&D movements regarding the previous year: Beginning R&D, stopping R&D, keeping R&D or holding without R&D.

In relation to previous experience in appropriation of returns associated with innovative activities, patents establish ownership rights, protecting innovators against imitators or potential free riders. To proxy this variable, we use a dummy that takes the value 1 if the firm has registered any patents in *t* and 0 otherwise.

[3] **A** more detailed explanation about the suitability of using the number and the duration of previous spells can be found in Fritjers (2002).

Technological degree is proxied by the classification of industries based on the OCDE taxonomy that distinguishes among manufacturing industries by their level of technological intensity. Additionally, the number of years in the current spell lets us analyze the probability of ceasing innovations considering the consecutive years with innovations. Finally, control variables are introduced: sectorial dummies, firm size in terms of employees and current year.

5. Main results

5.1. Survival analysis

Table 1 presents the probability of survival in innovation, distinguishing between product and process innovations. While the probability of survival in process innovation at least one year is more than 76%, this probability is around 70% for product innovation. These probabilities decrease up to 35% and 33.5% in the 5th year. However, the probability of survival in product is higher than in process in the 15th year (11.5% for process and 12.4% for product) and the difference is two points in the 20th year (6.2% for process and 8.2% for product). Although neither of the differences in the average duration of spells are noteworthy (2.409 years for process and 2.481 years for product under three years for both types of innovation[4]), the higher number of spells for process innovation compared wth product innovation confirms that process innovation is more usual than product innovation. However, there is not necessarily a direct relationship between frequency and persistence in innovation.

Given our supposition that the dynamics of product and process innovation might differ depending on the industry in which the firm operates, Table 1 shows the survival rates according to the technological level in the sector. As we can see, firms in high-tech industries have a higher probability of survival in product innovation, whereas firms belonging to a medium-tech sector hold a higher probability of survival in process innovation. Firms operating in low-tech sectors have a higher probability of survival in process innovation during the first few years, while this probability is higher for product innovation over time. Furthermore, the highest probability of survival after 20 years is also found in product innovation for firms in high-tech industries.

[4] Our results are comparable to those obtained in previous studies based on duration analyses (Geroski et al., 1997; Cabagnols, 2003; Jang and Chen, 2011).

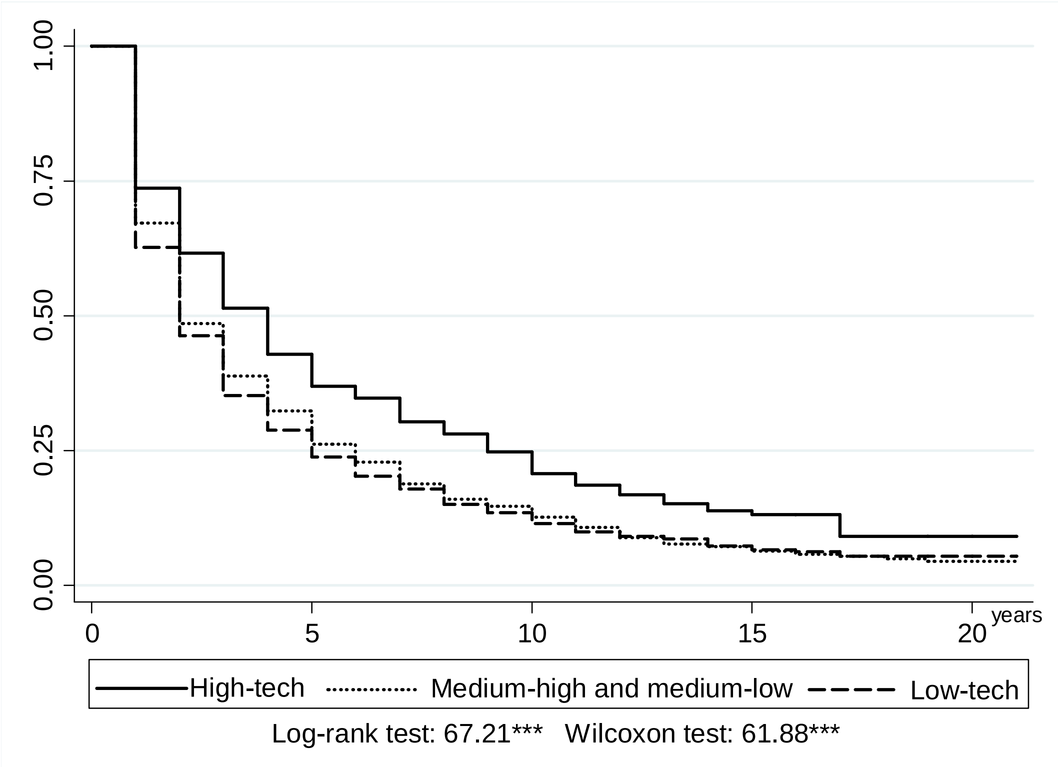
Table 1. Survival rates and descriptive statistics for spells in process and product innovation.

	Total manufacturing		High-tech Industries		Medium-tech Industries		Low-tech industries	
	Process Innov	Product Innov	Process Innov	Product Innov	Process Innov	Product Innov	Process Innov	Product Innov
1	0.760 (0.240)	0.706 (0.294)	0.760 (0.240)	0.770 (0.230)	0.754 (0.246)	0.673 (0.327)	0.757 (0.243)	0.700 (0.300)
5	0.354 (0.146)	0.335 (0.132)	0.356 (0.144)	0.409 (0.101)	0.357 (0.151)	0.293 (0.147)	0.344 (0.139)	0.335 (0.141)
10	0.169 (0.157)	0.171 (0.150)	0.175 (0.154)	0.210 (0.237)	0.188 (0.109)	0.119 (0.176)	0.141 (0.225)	0.208 (0.049)
15	0.115 (0.032)	0.124 --	0.096 --	0.159 (0.077)	0.141 --	0.091 --	0.093 --	0.134 --
20	0.062 --	0.082 --	-- --	0.124 --	0.076 --	0.042 --	0.058 --	0.102 --
Num. spells	5,253	3,726	888	734	2,093	1,479	2,197	1,475
Average num. spells by firm	2.223	2.061	2.268	2.027	2.350	2.189	2.126	1.978
Average spell duration	2.409	2.481	2.680	3.000	2.527	2.362	2.235	2.379
Num. Firms	3,161	2,402	532	480	1,227	925	1,377	999
Num. Observations	12,580	9,205	2,365	2,198	5,306	3,489	4,909	3,518

Note: Hazard rates in brackets

The survival functions also confirm the low degree of survival of innovation over the period 1990-2010 by industries (Figure 1). The decreasing slope of the function from 4th year onwards shows that the probability of survival decreases as long as the duration of the spell increases. These results lead us to the conclusion that persistence in innovation is low in the initial stages (the survival function decreases quickly), but after 5-6 years, survival rates remain nearly constant. Furthermore, we find significant differences among industries. From the 2nd year onwards, the survival curve of innovation in high-tech industries is above the curve of the rest of the sectors. Thus, high-tech manufacturers are more prone to consolidate innovation than medium and low-tech industries. In this regard, belonging to high–tech industries reduces the risk of ceasing innovative activities.

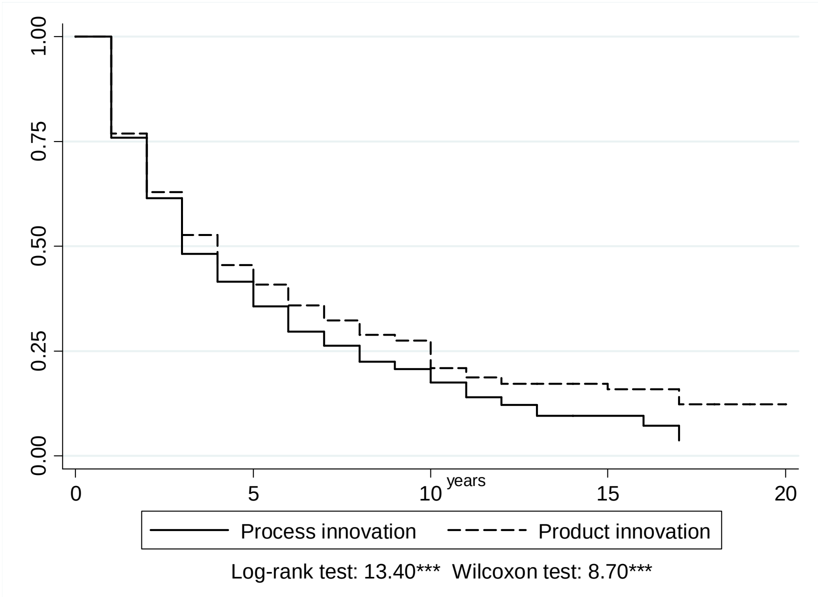
Figure 1. Survival functions of innovation by industries.



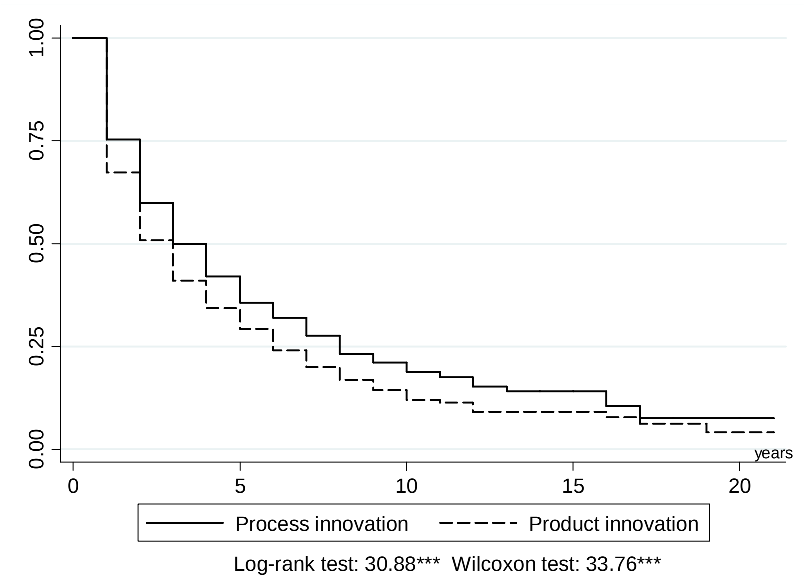
To complete the analysis carried out in Table 1, the survival curves of product and process innovations are compared by industries (Figure 2). High-tech industries are more persistent in product than in process innovations. For each year, the estimated survival rate is always lower for process innovators than for product innovators. Indeed, there are no firms innovating in process after 17 years and only 9.6% of firms maintain their process innovation for 15 years (15.9% in product innovation). By contrast, process innovation is more frequent and more persistent than product innovation in medium-tech industries over the whole period. Finally, an erratic innovative performance in low-tech industries is found. During the first 7 years, the survival rate is higher in process innovation but product innovation is more persistent afterwards.

Figure 2. Survival functions of process and product innovation by industries

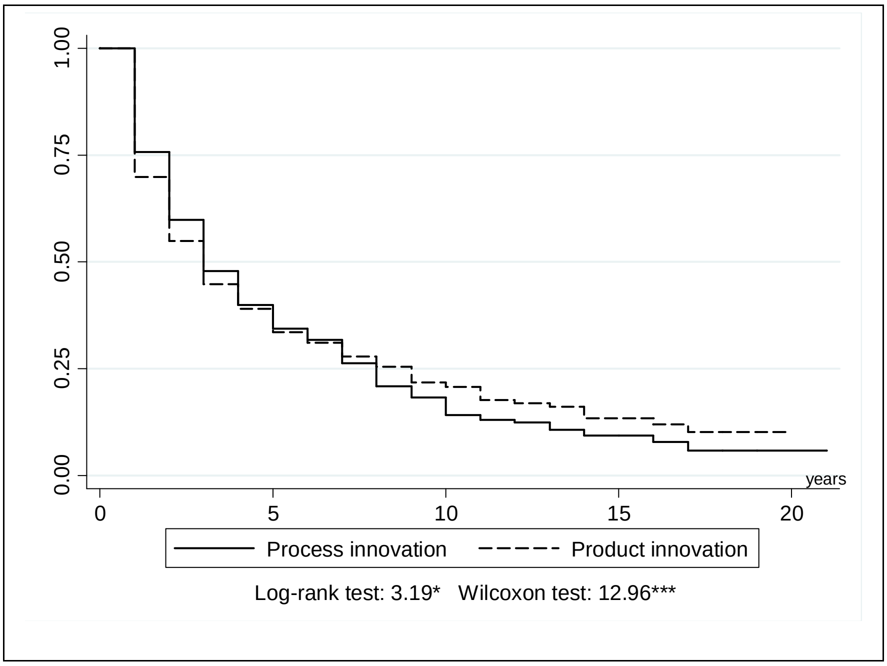
High-Tech industries



Medium-Tech industries



Low-Tech industries



5.2. Econometric results

Table 2 presents the results of the estimations with and without interactions. Three models are estimated. The first one (Model I) only includes the variables related to the previous innovation experience (state dependence); the previous spell duration (past dependence) and the number of previous spells (path dependence). In the second estimation (Model II), the rest of the explanatory variables related to the dynamic capabilities of firms are introduced. Finally, sector dummies are included (Model III).

Coefficients are shown in exponential form (odds ratios). In contrast to marginal effects, odds ratios are interpreted in multiplicative terms (Buis, 2010) or in other words, the rate of change in the hazard ratio derived from a one-unit change in the corresponding covariate[5]. The hazard ratio is greater than one if the corresponding coefficient negatively affects the duration of innovation, and *vice versa*. A ratio equal to one would imply no impact on persistence of innovation. Coefficients of interacted variables indicate the percentage difference between the impact of the explanatory variable with product innovation and the impact with process innovation.

Considering all the innovation spells (product or process) of a firm, the probability of stopping innovation (leaving the current spell) is 1.15 to-1.47 times more likely in the

[5] Interpreting coefficients in terms of marginal effects in non-linear models could provide erroneous conclusions (Ai and Norton, 2003; Hoetker, 2007)

case of product innovation than in process innovation. This result indicates a higher number of exits from the product innovation spells, but it does not mean that persistence in product innovation is lower than in process innovation. In fact, as the duration of the spell increases, the probability of exiting is 18% lower for the product innovation (variable *product innovation*logseq*). Therefore, in the initial years, it is easier for the firm to maintain the process innovation. Nevertheless, the probability of persistence increases if the firm is a product innovator in the middle and long term.

In relation to innovative experience (state dependence), the duration of the previous spell seems to have a higher impact on the exit probability of the innovation spell than the number of the previous spells, which is not significant (Model I). The higher the duration of the previous spell, the higher the duration of the current spell. In line with the empirical literature, we find a significant and positive past dependence between previous spell duration and survival in innovation for both types of innovations (H1 is accepted). This result suggests the past dependence behavior of innovation persistence. Nevertheless, the interaction of the variable with the type of innovation is not significant.

If we introduce the rest of the explanatory variables (Models II and III)**,** the number of previous spells significantly and negatively affects the probability of exiting. The higher the number of previous spells, the higher the exit rate of the current innovation spell. If we distinguish between both types of innovation, the coefficient is not significant (*variable product innovation*number of previous spells*)**,** which means that there is no significant ~~differences~~ in the impact of the number of previous spells according to the type of innovation.

Table 2. Results of random effects clog-log model

	Model I		**Model II**		**Model III**	
	Ia	**Ib**	**IIa**	**IIb**	**IIIa**	**IIIb**
	No interact	**Interact.**	**No interact**	**Interact.**	**No interact**	**Interact.**
Product Innovation (t.in) [(a)]	1.187*** (0.000)	1.150*** (0.003)	1.168*** (0.000)	1.477*** (0.000)	1.172*** (0.000)	1.244*** (0.000)
Log of duration of current spell (logseq)			0.958 (0.831)	0.946 (0.748)	0.952 (0.801)	0.979 (0.905)

Product innovation*Log of duration of current spell (logseq)				0.822*** (0.000)		0.819*** (0.000)
Previous spell duration of innovation	0.927*** (0.000)	0.926*** (0.000)	0.954*** (0.008)	0.951*** (0.055)	0.955*** (0.010)	0.950*** (0.087)
Number of previous innovation spells	0.984 (0.546)	0.962 (0.266)	1.082*** (0.008)	1.068* (0.055)	1.078** (0.010)	1.062* (0.087)
Product innovation*Previous spell duration of innovation		1.001 (0.971)		1.017 (0.545)		1.016 (0.567)
Product innovation*Number of previous innovation spells		1.058 (0.304)		1.032 (0.549)		1.023 (0.656)
Having patents			0.845*** (0.003)	0.942 (0.418)	0.850*** (0.004)	0.960 (0.585)
Product innovation*having patents				0.796** (0.0326)		0.816* (0.0549)
Beginning R&D activities[(b)]			0.831** (0.037)	0.740** (0.010)	0.830** (0.036)	0.737*** (0.010)
Product innovation* Beginning R&D activities				1.287 (0.153)		1.305 (0.131)
Keep doing R&D activities[(b)]			0.738*** (0.000)	0.735*** (0.000)	0.744*** (0.000)	0.746*** (0.000)
Product innovation*Keep doing R&D activities				1.029 (0.721)		1.012 (0.880)
Stopping R&D activities[(b)]			1.494*** (0.000)	1.405*** (0.000)	1.497*** (0.000)	1.405*** (0.000)
Product innovation*Stopping R&D activities				1.126 (0.323)		1.145 (0.264)
High tech[(c)]			0.860*** (0.005)	1.067 (0.314)		
Product innovation*High tech				0.641*** (0.000)		
Low tech[(c)]			0.892*** (0.007)	1.003 (0.954)		
Product innovation*Low tech				0.775*** (0.001)		
Constant	0.233*** (0.000)	0.236*** (0.000)	0.400*** (0.000)	0.376*** (0.000)	0.378*** (0.000)	0.376*** (0.000)
Year control			yes	yes	yes	Yes
Industry control					yes	Yes
Size control			yes	yes	yes	Yes
Log-likelihood	-10965 (0.000)	-10964 (0.000)	-10423 (0.000)	-10397 (0.000)	-10411 (0.000)	-10398 (0.000)
Rho	0.355 (0.000)	0.355 (0.000)	0.247 (0.000)	0.165 (0.000)	0.239 (0.000)	0.193 (0.000)
Number of firms	3,535	3,535	3,451	3,451	3,451	3,451
Number of spells	8,979	8,979	8,861	8,861	8,861	8,861

Observations	21,898	21,898	21,736	21,736	21,736	21,736

[(a)]Reference: Process innovation. ([b])Reference: Keeping without R&D activities. ([c])Reference: Medium-tech industries. (*)Clog-log model has been estimated with the hshaz Stata command.

Regarding the influence of R&D effort, the fact of starting to do R&D decreases the probability of exiting from innovation between 17-26%. Furthermore, being a continuous R&D performer (learning by doing effect) decreases the risk rate of stopping innovation around 25%. These results are in line with previous studies (Lelarge, 2006; Clausen et. al., 2011, Triguero and Córcoles, 2013). Finally, the decision to stop R&D activities negatively affect**s** the probability of leaving innovation between 40-50% (H2 is accepted). Therefore, being persistent in R&D has a great influence on the survival of innovations. Nevertheless, there are no significant differences according to the type of innovation, which lead**s** us to conclude that R&D activities have a similar effect on both innovations (H2a is rejected).

In addition, patents increase the probability of survival in the spell of innovation around 15% (coefficient "having patents" around 0.85 in specifications IIa and IIIa). Higher appropriability enhances persistence in innovation. If we distinguish between product and process innovation, we observe that this effect is only linked to product innovation (Model IIb and IIIb). The probability of exiting from product innovation for a firm with registered patents is notably lower than the probability of exiting from process innovation. Taking into account that the joint effect for both types of innovation is no longer significant**,** H3 is rejected. However, high technological appropriability is found for product innovation. Thus, H3a is accepted.

Finally, differences in innovation persistence are confirmed depending on the industries in which a firm operates (technological opportunities). According to OECD classification, we consider inter-industry differences of technology in Model II. Compared with firms in medium-tech sectors, firms in high-tech and low-tech sectors are very likely to persist in innovation. As we expected, firms in high-tech industries are more persistent in product innovation (H4a accepted). This result is similar to Clausen's (2011). Surprisingly, we find the same result for firms operating in low-tech sectors. Similar to the interpretation of the influence of appropriability on joint persistence, we have to reject H4 because of the lack of significance when interactions are considered. That means that a higher effect of technological opportunities and appropriability on persistence in product innovation is found. In other words, we have to accept H1a partially. Although there are no significant differences in the effect of the number of previous spells on product and process innovation, results found in prior models confirm the path character of product innovation noted by Artz et al. (2010).

6. Conclusions

This paper explores the influence of previous experience and learning capabilities on survival in innovation activities in Spanish manufacturing firms during the period 1990-2010. Using discrete time-duration analysis, we explicitly distinguish the differences in persistence between process and product innovations in a period of 20 years.

We confirm that in spite of the fact that firms tend to maintain process innovation during the initial years, the probability of persistence is higher in product innovation over time. That means that the probability of exiting the current innovation spell is lower in product innovation as the duration of this spell increases. However, being persistent in innovation in the past (long previous spells) improves the probability of being persistent at the current moment for both types of innovation, taking into account innovation experience. Therefore, the past-dependence behavior of innovation is confirmed. However, there are not any significant differences between product and process innovation. On the other hand, the higher the number of previous spells, the higher the rate of exiting the current innovation spell. That means that firms with erratic behavior in the past in terms of innovation have a lower probability of being stable innovators. Similar to the effect of duration of the previous spell, there are no significant differences according to the type of innovation.

These findings have implications for policy makers because the strategy choice in the past may affect the persistence of their innovative activities. Firms that have a continuous experience in product or process innovation have a lower probability of ceasing innovation than firms that have erratic experience in innovation. "What the firm can hope to do technologically in the future is narrowly constrained by what it has been capable of doing in the past" (Dosi, 1988, p. 1130).

We also investigate the influence of several drivers on persistence in innovation, taking into account the theoretical framework built on evolutionary approaches. Past innovation affects the degree to which firms do innovations in the current period but also enables firms to learn and face market changes and exogenous factors. In particular, we have considered additional drivers related to learning capabilities of the firm, such as cumulative R&D effort, appropriability conditions and technological opportunities. The models report similar results in the alternative specifications, confirming the robustness of our estimations. First, we confirm that being a continuous R&D performer increases the duration of innovation but there are not any significant differences between product and process innovation. At the same time, the decision of stopping R&D activities negatively affects the probability of stopping innovation. Second, we highlight the positive influence of previous experience in appropriability on innovation, although this effect is only found in product innovation. Finally, firms that operate in high-tech sectors have a high probability of being persistent.

To sum up, the past and path dependent behaviour of innovation have been showed. Experience in innovation gives a competitive "premium," reducing the risk of ceasing innovation among Spanish manufacturing firms. Furthermore, the probability of survival increases if the firm is specialized in product innovation in the mid and long term. Nevertheless, we cannot confirm significant differences due to previous experience between product and process innovation. Product innovation is associated with high levels of appropriability given that patents are usually the protection mechanism used for this kind of innovation. Furthermore, product innovation is more persistent in high-tech sectors but also in low-tech sectors. We believe that further research is needed to explain the different behavior of leading and innovative firms in each industry to reveal to what extent firms that innovate once (it seems that does not matter in product or process innovations) have a higher probability of innovating again in subsequent periods.

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Appendix

Table A.1. Definition of variables.

Variable	Definition
	Dependent variable
Hazard rate of current spell of innovation	Categorical variable indicating the discrete exit probability of a spell of product or process innovation. It is equals 1 when firm innovates in "t" and does not innovate in "*t+1*", zero otherwise.
	Type of innovation
Type of innovation (*t.in*)	Categorical variable that identifies the type of innovation of the current spell. It is equals 1 if the current spell is a product innovation spell and 0 when the current spell is a process innovation spell.
	State dependence variables
Duration of previous spell	Duration (in years) of the previous process or product spell at the beginning of the current spell.
Number of previous spells	Number of previous process and product spells at the beginning of the current spell.
	Explanatory variables
Having patents	Categorical variable. Having patents=1 if the firm has registered any patent in t, zero otherwise.
R&D activities	Categorical variable considering all R&D movements of the firm in "*t*" compared to "t-1". R&D activities =0 if firm Keeping without R&D (non R&D in *t-1* and non R&D in *t*) =1 if firm Beginning R&D activities (non R&D in *t-1* and R&D in *t*) =2 if firm Keeping R&D activities (R&D in *t-1* and R&D in *t*) =3 if firm stopping R&D activities (R&D in *t-1* and non R&D in *t*)
Technological degree	Industry classification according to technological degree (OECD classification). • Low technology industries=0 includes: Meat products; Food and tobacco; Beverage; Textiles and clothing; Leather, fur and footwear; Timber; Paper; Printing; Furniture; Other manufacturing. • Medium-Technology=1 (Low-Medium and High-medium OECD classification): Plastic and rubber products; Nonmetal mineral products; Basic metal products; Fabricated metal products; Machinery and equipment; Vehicles and accessories; Other transport equipment. • High technology industries=2. This category includes: Chemicals and pharmaceuticals; Computer products, electronics and optical; Electric materials and accessories.
Log of duration of current spell (logseq)	Variable that uniquely identifies the number of periods in the current spell, in logs.
	Control variables
Id. Spell	Control variable that uniquely identifies each spell of product or process innovation. Reference unit in panels for survival models.
Id. Seq	Control variable that uniquely identifies the number of periods in the current spell of product or process innovation. For each spell. Max: Id. Seq = duration of spell. Time reference in panels for survival models.
Size	Categorical variable. Size=1 for medium and small firms (1 to 199 employees) Size =2 for large firms (200 or more employees).
Industry (NACECLIO)	Categorical variable identifying the manufacturing sector for each firm: 1 Meat products; 2 Food and tobacco; 3 Beverage; 4 Textiles and clothing; 5 Leather, fur and footwear; 6 Timber; 7 Paper; 8 Printing; 9 Chemicals and pharmaceuticals;

	10 Plastic and rubber products; 11 Nonmetal mineral products; 12 Basic metal products; 13 Fabricated metal products; 14 Machinery and equipment; 15 Computer products, electronics and optical; 16 Electric materials and accessories; 17 Vehicles and accessories; 18 Other transport equipment; 19 Furniture; 20 Other manufacturing.
Year	Year of the current spell. Values: 1990-2010.

Table A.2. Descriptive statistics

	Obs. (# firms)	***Avg***	**Std. error**	**Max.**	**Min.**
Dependent variable (hazard rate)	21,898 (3,535)	0.208	0.406	1	0
Type of innovation	21,898 (3,535)	0.422	0.494	1	0
Duration of previous spell	21898 (3,535)	0.957	1.852	17	0
Number of previous spells	21898 (3,535)	0.571	0.858	6	0
Having patents	21,849 (3,535)	0.127	0.333	1	0
R&D activities	21,898 (3,535)	1.373	0.995	3	0
Technological degree	21,785 (3,451)	10.706	5.472	20	1
Log duration of current spell	21,898 (3,535)	0.755	0.766	3.045	0
Id. Spell	21,898 (3,535)	7856.207	4322.234	14,878	2
Id.Seq	21,898 (3,535)	2.948	2.803	21	1
Size	21,898 (3,535)	1.470	0.499	2	1
Industry	21,785 (3,451)	10.707	5.472	20	1
Year	21,898 (3,535)	1999.705	6.099	2010	1990