

Technological innovation persistence in Spanish manufacturing: Product *versus* Process Innovation

David Córcoles

University of Castilla-La Mancha
Department of International
Economics
Faculty of Economics and Business
02071, Albacete (Spain)
Phone: 34 967 59 92 00 (ext. 2371)
e-mail: david.corcoles@uclm.es

Ángela Triguero-Cano

University of Castilla-La Mancha
Department of International
Economics
Faculty of Economics and Business
02071, Albacete (Spain)
Phone: 34 967 59 92 00 (ext. 2380)
e-mail: angela.triguero@uclm.es

Maria C. Cuerva

University of Castilla-La Mancha
Department of International
Economics
Faculty of Economics and Business
02071, Albacete (Spain)
Phone: 34 967 59 92 00 (ext. 2371)
e-mail: mariac.cuerva@uclm.es

ABSTRACT

The main purpose of this paper is to analyse what is the influence of previous experience on the survival in innovation activities distinguishing between product and process innovation. Our empirical strategy consists in the estimation of discrete-time duration models using a large representative sample of Spanish manufacturing firms for the period 1990-2010. We find true state dependence in both types of innovation, although previous experience is more important for process than for product. Accumulated R&D and the fact of operating in a high- tech sector are crucial for persistence in product innovation. We also identify previous experience as exporter to consider the impact of internationalization on innovative persistence. The results indicate a positive relationship between the learning capabilities of exporting and persistence in both types of innovations.

Key words: persistence in innovation, product innovation, process innovation, discrete-time duration models, panel-data.

JEL code: L26, L60, O31

1. Introduction

The phenomenon called “persistence of innovation” is an important topic in the literature on innovation (Antonelli et al. 2009). The persistence of innovative behavior is identified if a firm which innovates once has a higher probability of innovating again in subsequent periods. Thus, 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 as proxy variables of innovative activity the number of patents (Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001; Cefis, 2003; Cabagnols, 2006), the R&D effort (Mañez-Castillejo et al. 2009; Peters, 2009; Triguero and Córcoles, 2013) or innovation output indicators (Flaig and Stadler, 1994; Rogers, 2004, Duguet and Manjon, 2004; Peters, 2009; Raymond et al. 2010; Triguero and Córcoles, 2013). But, as far as we know, only 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, instead of proxies of innovative persistence (Geroski et al., 1997; Le Bas et al., 2003; Cabagnols, 2003; Jang and Chen, 2011). Therefore, in this paper we model the persistent innovative activity by the number of successive years in which a firm innovates.

Although the duration analysis has been used in prior work to distinguish between persistent and occasional innovators, our purpose is to determine the survival in innovation activities using discrete-time duration models. This new methodology enables us to solve the main limitations of continuous-time duration models typically used in the previous literature (unobserved heterogeneity and the proportional hazard assumption).

The literature about persistence in innovation has also identified differentiated patterns of persistence when different types of innovation activities (new products, processes, organization methods) are considered. However, the differences between persistence of process and product innovations are not at all present in the literature review. Most of the studies recognize that there is a general degree of association or complementarity between product and process innovation (Reichstein and Salter 2006). Nevertheless, a different pattern of persistence across product and process innovation should be considered. Some related literature indicates that product innovation is more persistent than process innovation (Martínez-Ros and Labeaga, 2009; Antonelli et al.,

2012a). Nevertheless, we feel that the understanding of the different drivers of persistence in product and process innovation remains limited. In this regard, we have tried to do a more thorough consideration of this topic. The availability of a panel-data of more than 20 years allows us to do this distinction. Building upon the dynamic capabilities framework, we present a model that examines the role of learning capabilities in the innovation persistence. In this sense, we argue that the ability of a firm to be constant in R&D activities, to maintain a good degree of internationalization (exports) and register patents (appropriability conditions) is crucial to its innovative behavior but they may affect differently the persistence in innovation considering both types of innovative activities. Hence, the main purpose of our research is to test whether the 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 a new empirical methodology that solves some of the problems of prior work based on duration analysis to measure persistence in innovative activity. We model the 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. Hence, we identify differentiated patterns of persistence depending on past experience in each type of innovation. Third, we measure separately lagged and occurrence dependence in product and process innovations. Finally, we study how other factors proxied by firm-level and sector-level characteristics affect the degree of persistence. In particular, we include the influence of the persistence of exporting instead of the exporting behaviour in a specific year. As far as we know, this is the first analysis that relates persistence in export to persistence in innovation.

The reminder of the paper is organized as follows: section 2 reviews the empirical literature about persistence in innovation and purposes 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 5 concludes.

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

There is an increasing literature about persistence in innovation but mainly focused on explaining the probability of doing R&D or innovation without distinguish different types of innovation. As far as we know only few related studies distinguish among the degree of persistence of process and product innovations.

Given the complexity of innovation process, firms have to decide their innovation strategy and choose between product innovations, process innovations or both. Although most of the studies recognized that there is a general degree of association 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) or even persistence is found for product but not for process innovation (Parisi et al. 2006).

According to Antonelli et al. (2012b), two quite different explanations of the innovation persistence could be remarked. The first one links the innovation persistence with a process 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 treats to measure the observed persistence attributable to the fact of innovating in the past and not to other firm-specific factor (past dependence). The second one is closely related with the resource based theory of the firm where the innovation persistence is linked with the internal characteristics of firms and changing characteristics of the context into which firms are localized (path dependence).

Both theoretical perspectives are going to be considered in this work. On the one hand, path- dependence provides a framework to model 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 true state persistence (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 to explain the differences

between persistence in product and process innovations on a sample of 451 Italian manufacturing companies during the years 1998-2006. While the persistence of process innovations seems to be characterized by elements of path dependence, persistence in product innovations seems stronger and closer to past dependence. In other words, business cycles would affect persistence of process innovations. On the other hand, the persistence of product innovations would be more related to the dynamic capabilities of the firm and its ability to learn and use the knowledge. According to these results, we formulate the following hypotheses:

Hypothesis 1 (H1): The previous experience in innovation enhances persistence in innovation (past dependence)

H1a: The previous experience in process innovation enhances persistence in innovation to a lower extent than past experience in product innovations (past dependence).

Past innovation affects the degree to which firms do innovation in the current period but they can react due to learning by doing or changes in exogenous factors. Indeed, the firm's learning capabilities play a crucial role in generating innovations and they serve to test path dependence. In this work we consider that firms accumulate knowledge as a strategic asset through R&D, appropriation of returns of innovation (patents) and exporting. The resource based view (RBV) of the firm provides a framework to explore the role of these learning capabilities in innovation persistence. Part of capabilities is captured by the firm's internal R&D efforts. The influence of R&D has been showed a stronger predictor of persistence in innovation in the previous literature. Several R&D indicators enable to explain current innovation output by past innovation input (Raymond et al., 2010). In this sense, a positive relationship is found between persistence in innovation and lagged R&D (Lelarge, 2006; Triguero and Córcoles, 2013). However, like already suggested by Audretsch (2003), innovation inputs and outputs could not be correlated because "R&D reflects only the resources devoted to producing innovative output, but not the innovative activity actually realized" (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) foster or not persistence in innovation because then continuous R&D performers should increase the probability of successful innovation. Being a continuous performer increases the probability of

enhancing knowledge accumulation and persistence in innovation. This argument is based on the “success breeds success” argument (Flaig and Stadler, 1994; Geroski et al., 1997). Furthermore, knowledge accumulation enhances the probability of future innovation and persistence in innovative activities by the “learning by doing” effect (Peters, 2009).

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

Another important factor that should be considered is the appropriability or the degree to which a firm can protect its innovative capabilities from its competitors through patents, trade secrets or utility models. The evidence suggests that appropriability conditions are one of the factors shaping the probability to innovate. In this sense a minimum degree of appropriability is necessary to motivate innovation (Dosi et al., 2006). Although the individual effect on persistence has not often considered in the literature, according to Le Bas et al. (2011) appropriability conditions have a strong effect on persistence in process innovation in persistent and sporadic innovators but curiously only affects the persistence in product innovation in the group of occasional innovators. Therefore, the strength of the appropriability regime affects positively the degree of persistence in innovation. Thus, persistence in innovation is lower for firms with weakness of appropriability conditions than for those with strength of appropriability conditions. 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 innovation.

Apart from the internal firm-characteristics more intimately related to technological process, other factors could influence the probability to survive as persistent innovators. Export activity and innovation are likely to be inter-related (Rogers, 2004). The relationship between both variables has been analyzed to test the causality link. On the one hand, Roper and Love (2002), Cassiman et al. (2010) or Becker and Egger (2013) conclude that product innovation is more determinant in the exporting behavior of a firm than is process innovation. On the other hand, the literature of persistence shows

that export performance is an important determinant for innovating persistently (Peters, 2009), in particular, in the case of product innovation (Martínez-Ros and Labeaga, 2009). According to these results we believe that the degree of internationalization contributes positively to persistence in innovation through the acquisition of new knowledge and external appropriation of innovation. Nevertheless, we consider that it is more relevant to observe the export behavior of the firm across time rather than to know if the firm exports or not in a specific year. Thus, we hypothesis that:

Hypothesis 4 (H4): A persistent export activity affects positively the degree of persistence in product and process innovation.

Finally, differences in innovation might be attributed to industry heterogeneity (Peters, 2009). Sectors differ in their commitment of resources to search activities and in the rates at which they generate new products and processes of production (Dosi, 1988, p.1125). In this regard, the essential role of technological opportunities is usually considered in the literature of innovation. Technological opportunities assess the ease of innovation in a particular sector, thus they account for industry differences in R&D intensity (Cohen and Levinthal, 1989). These approaches are mainly associated with the opportunity for specific innovations under particular industry-level conditions. Firms operating in high tech industries will tend to be closer to the technological frontier and therefore more likely to be persistent in innovation (Lelarge, 2006; Raymond et al. 2010). Other works similarly conclude that firms belonging to high-tech industries have more chance of innovating persistently (Huang and Yang, 2010). Since we need to take into account the technological level in the sector in which the firm operates to explain the different determinants of persistence in innovation, we assume that:

Hypothesis 5 (H5): Technological opportunities are expected to play a significant role for process and product innovation persistence.

Moreover, we believe that the dynamics of product and process innovation could differ depending on industry in which the firm operates. Similarly to Clausen et al. (2012), we expect to find differences on the persistence of product and process innovation within high-tech versus low-tech firms in the sense that high technology is

more assimilated to product innovation whereas low technology is more connected to process innovation. Thus, we hypothesize that:

H5a: Persistence in product innovation could be higher for firms operating in high-tech industries than for firms operating in low tech-industries.

H5b: Persistence in process innovation could be higher for firms operating in low-tech and/or medium-tech industries than for firms operating in high-tech industries.

3. Methodology.

Following Geroski *et al.* (1997), we define the degree of innovation persistence through spells, in other words, as the number of consecutive years during which the firm has an innovative output.

The main aim of empirical studies of duration data is to analyze 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” and in continuous terms, the “hazard” function. In formal terms, we define the hazard rate as the probability of a firm of ceasing to be an innovator at the 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 censored observations are included) and “*h_i*” as the number of firms that interrupt innovation exactly in “*t*”, we can calculate the hazard rate in the following way:

$$\phi(t) = \Pr(T = t | T \geq t) = \frac{\Pr(T=t)}{\Pr(T \geq t)} = \frac{h_i}{n_i} \quad (1)$$

From the expression 1, we define the survival function as the complementary distribution function of the hazard rate:

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

(*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*”) we can calculate the

hazard and survival functions using the Kaplan-Meier (1958) non-parametrical approach. Note that this method controls for right-censoring problem but not for the left-censoring problem. Given the random sample of innovative manufacturing firms, we calculate the number of consecutive years of innovation for each one (see Kiefer, 1988). 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. 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. Although this methodology has been often used in labour economics, it has been extended to other economic fields in the last years¹. In relation to innovation, the previous studies applying this methodology have usually taken into account the duration of patents (Geroski et al., 1997; Le Bas et al., 2003; Cabagnols, 2003; Jang and Chen, 2011).

Note that when we apply a duration model we do not measure the unconditional probability of a given spell duration (e.g. the probability of maintaining an innovation exactly five years) but 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 “hazard rate” (see equation 1). The general model specification is:

$$\phi(t)=f(X) \tag{3}$$

where X is a vector of determinant factors including: the previous spell duration, the number of previous spells, the cumulative R&D expenditures, the sector classified by technological intensity, the patents, the survival of exports and other control variables such as the years in the current spell or the firm’s size.

The literature that analyses persistence in innovation from duration models has used two types of different methodologies: semi-parametric Cox proportional hazards models (Cabagnols, 2003) or Weibull duration models (Geroski et al., 1997; Le Bas et al.,

¹ I.e., Obashi (2010) and Hess and Persson (2011b) in the discipline of international economics; Collier (2005) in labor economics.

2003; Jang and Chen, 2011). Nevertheless, recent studies point out that these models may be inappropriate (Brenton et al., 2010; Fugazza and Molina, 2011). On the one hand, both models assume that duration data are continuous whereas innovation data usually are referred to discrete-time intervals (years)². On the other hand, Cox models do not control for the unobserved heterogeneity (or frailty). Finally, the assumption of proportional hazards in continuous-time models is inaccurate. It is not plausible that the effects of the determinant factors would be proportional at different moments of spell duration.

The use of discrete-time models solves these problems (Hess and Persson, 2011a) because this methodology does not have difficulties with the ties, controls for unobserved heterogeneity and relaxes the assumption about the proportional hazards. Taking into account these advantages, two types of discrete-time models are estimated: clog-log and probit models. The clog-log model determines frailty with a more flexible functional form than the probit model (Heckman and Singer, 1984). Probit model does not imply to assume proportional hazards (Sueyoshi, 1995).

4. Data and variables.

4.1.Data

For 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 around 1,800-2,000 firms surveyed yearly for all the industrial sectors that maintain a high representativeness of the Spanish manufacturing sector over the whole population. The coverage of the data set is mixed: a random sample for small companies (with less than 200 employees) and a complete sample for large firms (with more than 200 employees).

The ESEE dataset allows to construct innovative spells considering all types of innovation as well as to take into account separately process and product innovations. In addition, it also allows to identify other influencing factors related with our theoretical framework.

² The continuous-time models may result in biased coefficients and standard errors because the non-continuity properties of the innovative activities lead to numerous short spells which entail many tied survival times (Hess and Persson, 2011b). For this reason it is more suitable the use of discrete-time duration models (Cox and Oakes, 1984).

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 spell depending on the type of innovation considered: product, process or both (see Table in the Annex 1).

Explanatory variables

Following the theoretical background, we measure the previous experience in innovation (past dependence) through the duration of the previous spell and the number of previous spells. Both variables enable us to measure the effect of innovative experience, or true state dependence, on the current stability of innovation (Joyce, 2005; Shao et al., 2012) and to distinguish between lagged dependence and occurrence dependence (Doiron and Gørgens, 2008). On the one hand, lagged 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, occurrence 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 persistence³.

The existence of sunk costs associated to R&D spending justifies the inclusion of accumulated R&D expenditures over sales from initial to current year. In this sense, we have to remember that cumulateness means that technological capabilities in the present are the basis for future innovations and their existence encourages the firm to adopt a persistent innovation strategy.

³ More detailed explanation about the suitability of using the number and the duration of previous spells can be found in Fritjers (2002). In broad terms, there is no risk of endogeneity because the dependent variable and the proxies used have a different nature. The dependent variable (hazard rate) is a conditional function of density in t-time whereas the number and the duration of previous spells are referred to cumulative and unconditional values measured before starting the current spell. Additionally, from an econometric point of view, considering state dependence provides more efficient estimations because it allows us to control the effect of multiple spells (Joyce, 2005).

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

Export experience is proxied by the survival probability of exports in the current year. This measure enables us to identify previous experience of the firm as exporter. In particular, we know how long the firm has been exporting without interruption. Thus, we take into account the influence of firm's previous experience in international markets and its potential learning capabilities acquired by exporting on the persistence in innovation.

Finally, we consider the classification of industries based on the OCDE taxonomy that distinguishes among manufacturing industries by their level of technological intensity⁴. Additional control variables are introduced: sectorial dummies, firm size in terms of employees and the number of years in the current spell of innovation.

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 of two points in the 20th year (6.2% for process and 8.2% for product). Although the differences in the average duration of spells are neither noteworthy (2.409 years for process and 2.481 years for product- below three years for both types of innovation⁵), the higher number of spells for process innovation than for product innovation confirms that process innovation is more usual than product innovation. Thus, process innovation is more frequent but there is not a necessary relationship between frequency and persistence in innovation.

⁴ High and medium-high-technology industries include Chemicals and pharmaceuticals; Machinery and Equipment; Computer products, electronics and optical; Electrical materials and accessories; Vehicles and accessories, and Other transport equipment. Low and medium-low technology industries include Meat products; Food and tobacco; Beverage; Textiles and clothing; Leather, fur and footwear; Timber; Paper; Printing; Plastic and rubber products; Nonmetal mineral products; Basic metal products; Fabricated metal products; Furniture; and Other manufacturing.

⁵ Our results are comparable to those obtained in previous studies based on duration analyses (Geroski et al., 1997; Cabagnols, 2003; Jang and Chen, 2011).

Given that we consider that the dynamics of product and process innovation could differ depending on industry in which firm operates, we also present in Table 1 the survival rates according to the level of technology specific to the sector. Firms in high-tech industries have a higher probability of survival in product innovation, whereas firms belonging to medium-tech sector maintain 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 years while this probability is higher for product innovation as time goes on. The highest probability of survival after 20 years is found in product innovation for firms in high-tech industries.

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

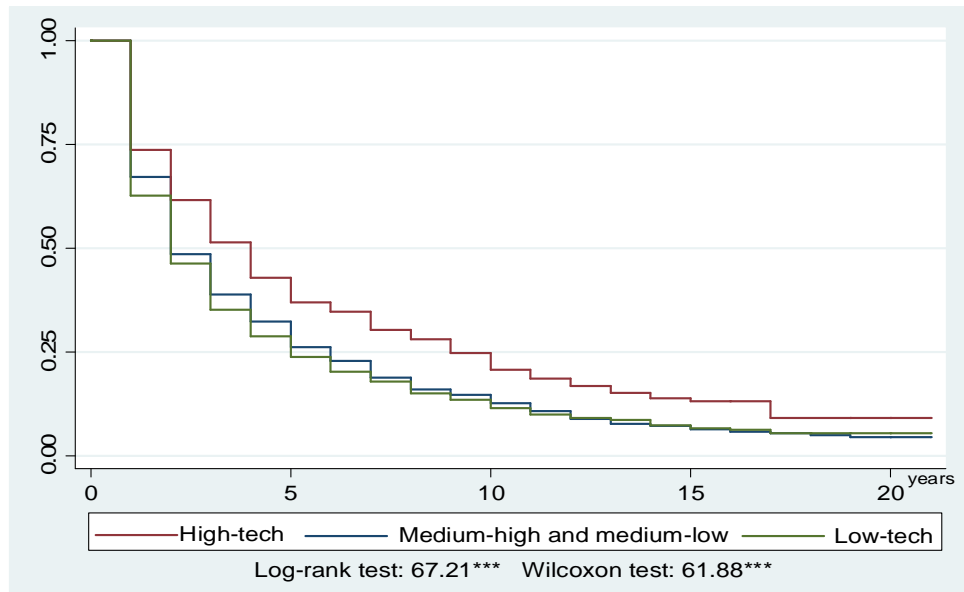
	Total manufacturing		High-tech Industries		Medium-tech industries		Low-tech industries	
	Process Innov	Product Innov	Process Innov	Product Innov	Process Innov	Product Innov	Process Innov	Product Innov
1	0.760 (0.240)	0.706 (0.294)	0.760 (0.240)	0.770 (0.230)	0.754 (0.246)	0.673 (0.327)	0.757 (0.243)	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 confirm also the low degree of survival of innovation across 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 spells increases. These results allow us to lead to the conclusion that persistence in innovation is low initially (the survival function decreases quickly), but after 5-6 years, survival rates remain nearly constant. Furthermore, we find significant

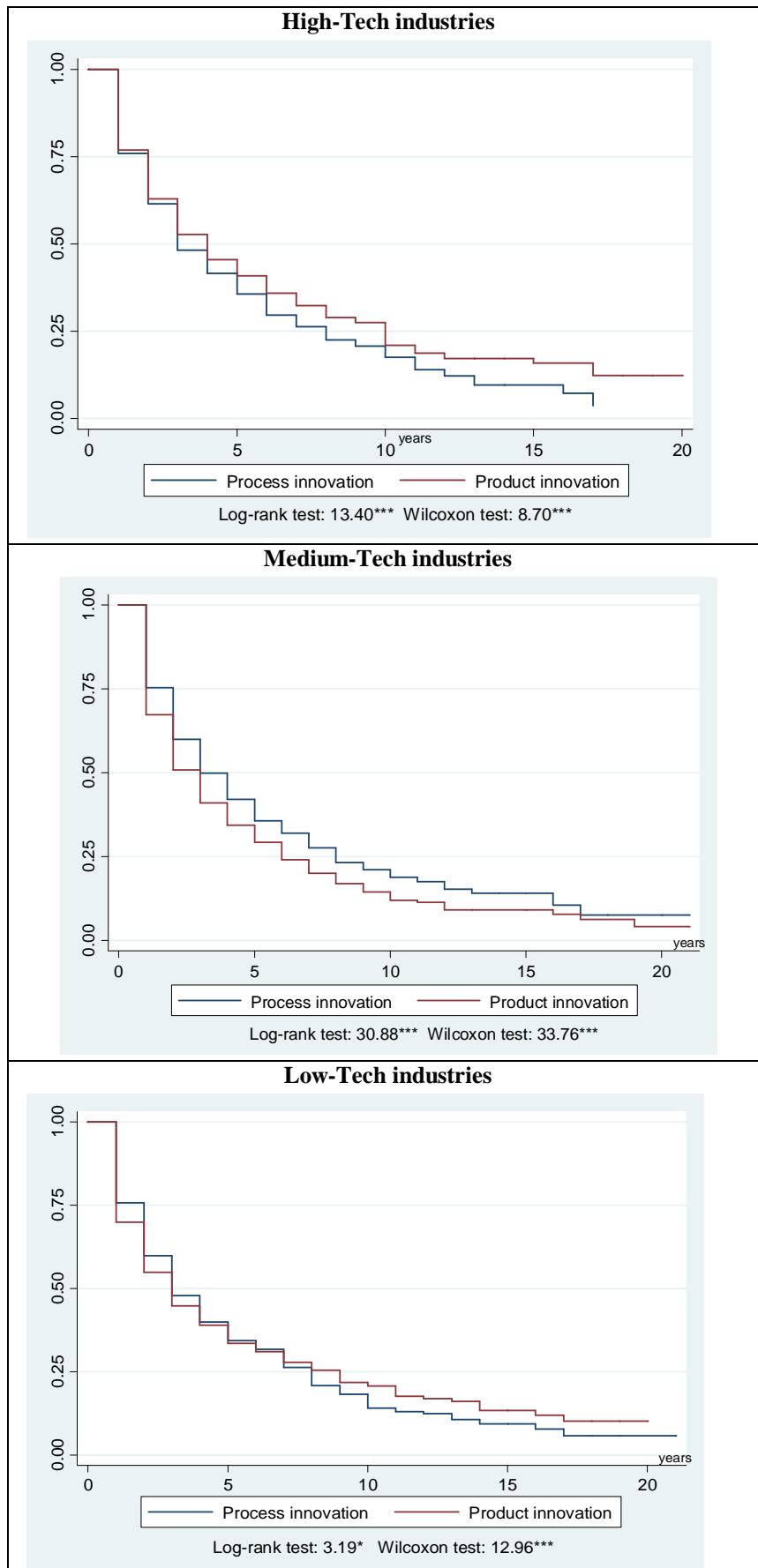
differences among industries. From the 2nd year onwards, the survival curve of innovation in high-tech industries is above the curve of the rest of sectors. Thus, high-tech manufactures are more prone to consolidate innovation than medium and low-tech industries. In this sense, being in high-tech industries reduces the risk of ceasing innovative activities.

Figure 1. Survival functions of innovation by industries



To complete the analysis made with Table 1, we compare the survival curves of product and process innovations 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). On the opposite side, process innovation is applied more frequently and more persistently than product innovation in the medium-tech industries across the whole period. Finally, we find an erratic innovative performance in low-tech industries. During the first 7 years, the survival rate is higher in process innovation but afterwards product innovation is more persistent.

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



5.2. Econometric results

Table 2 presents the results of clog-log and probit models taking into account for the construction of the dependent variable both types of innovations. Coefficients are shown in exponential form in the clog-log model. That means they can be interpreted in terms of the rate of change in the hazard ratio derived from a one-unit change in the corresponding covariate. 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. Additionally, the probit models are presented in marginal effects which express the change in the dependent variable (the probability of ceasing innovation) when the explanatory variable varies in one unit⁶. In this case a negative (positive) sign indicates a negative (positive) impact on the hazard rate or, in other words, a positive (negative) impact on the survival of innovation. Both of them allow us to compare coefficients among the different estimations.

First, we analyze the influence of being a persistent product or process innovator on the hazard rate of total innovation at moment t . To do this, we introduce the variables “duration of previous spell” and “number of previous spell” for each type of innovation. In line with the empirical literature, we find a significant and positive lagged dependence between the previous spell duration and the survival in innovation for both types of innovations (Hypothesis H1 is accepted). Being persistent in innovation in the past (long previous spells) improves the probability of being persistent at the current moment. Nevertheless, we find differences according to the number of previous spells. Results show negative occurrence dependence for process innovation. The higher the number of previous spells, the higher the rate of exit of the current innovation spell. On the contrary, these coefficients are not significant for product innovation. If firms tend to repeat past innovative patterns, the negative occurrence dependence suggests that process innovation is most applied but less persistent (a higher number but shorter spells) than product innovation. This result confirms the lower persistence of process innovation in the long run. Thus, the hypothesis H1a is accepted.

⁶ For the categorical variables marginal effect computes the probability of a discrete time in the values of the explanatory variable.

Table 2. Clog-Log and Probit models distinguishing among lagged and occurrence dependence of product and process innovative strategies

		Model with frailty (Exponential form) Clog-Log model* Discrete time			Probit model Discrete time Model with frailty No proportional hazards (Marginal effects)		
		model 1	Model 2	model 3	model 4	model 5	model 6
Lagged dependence	Previous spell duration for process innovation	0.969** (0.030)	0.962** (0.045)	0.967** (0.023)	-0.007** (0.029)	-0.010** (0.022)	-0.007** (0.0223)
	Previous spell duration for product innovation	0.918*** (0.000)	0.890*** (0.000)	0.927*** (0.000)	-0.017*** (0.000)	-	-
Occurrence dependence	Number of previous spells for process innovation	1.106***	1.143***	1.084***	0.021***	0.029***	0.018***
	Number of previous spells for product innovation	0.963 (0.245)	0.963 (0.387)	0.972 (0.393)	-0.010 (0.170)	-0.012 (0.237)	-0.007 (0.291)
	High ^a	0.755*** (0.000)	0.691*** (0.000)		-0.054*** (0.000)	0.078*** (0.000)	-
	Medium ^b	1.068** (0.047)	1.097** (0.033)		0.015** (0.033)	0.019* (0.070)	
	Low ^c	1.144*** (0.000)	1.194*** (0.000)		0.028*** (0.000)	0.043*** (0.000)	
	Sector dummies			Yes			yes
	Years in the current spell	0.642*** (0.000)		0.643*** (0.000)	-0.085*** (0.000)		-
	Size	0.591*** (0.000)	0.510*** (0.000)	0.593*** (0.000)	-0.107*** (0.000)	0.153*** (0.000)	-
	Constant	0.500*** (0.000)	0.206*** (0.000)	0.410*** (0.000)			-
Observations		16,123	16,123	16,123	16,123	16,123	16,123
Spells		5,807	5,807	5,723	5,807	5,807	5,723
Log likelihood		-8424.942	-	-	-8427.239	-	-
			8625.015	8354.310		8434.626	8357.429

(^a)Reference: Medium and Low industries. (^b)Reference: High and Low industries (^c) Reference: High and Medium industries. (*)Clog-log model has been estimated with the hshaz Stata command.

Table 2 shows similar results in the clog-log and the probit models for the specifications considered. According to OECD classification, we distinguish by the degree of technology of industries in the specifications (1) and (4). The fact of operating in a high-tech sector is a key factor for increasing the probability of survival of innovation (significant coefficients at the 99% level and attached coefficient below one in the clog-log and negative in the probit). The contrary occurs with firms belonging to medium and low-tech industries. In the specifications (2) and (5) the time-variable “years in the current spell” is omitted and the results do not change. Finally, we include sector dummies in the specifications (3) and (6) instead of OECD classification of

industries to check the robustness of our results. Again, we obtain similar results to the previous specifications.

In order to find relevant differences among the determinants of persistence in product and process innovations, Table 3 shows the different specifications taking into account separately both types of innovation. As well as the explanatory variables considered in Table 2 (state dependence and control variables), we have considered additional drivers of persistence in innovation related to the learning capabilities of the firm such as the input of the innovation process (cumulative R&D effort), the potential appropriation of returns of innovation (accumulated appropriability proxied by the registered patents) and the survival in foreign markets. In broad terms, clog-log and probit models report similar results in the alternative specifications confirming the robustness of estimations.

According to the previous experience (state dependence), coefficients show that firms tend to repeat their innovative pattern across time. The higher the duration of the previous spell, the lower the probability of exit of the current innovation spell (positive lagged dependence). Although coefficients are similar in value and sign for product and process innovation, the significance only remains at the 99% level for process innovation. In line with results of Table 2, we find a negative relationship between the number of previous spells and the duration of the current spell (negative occurrence dependence) but only significant (at 90% -95% level) for process innovation. Therefore, previous experience is more conclusive for process than for product innovation.

In regard to the R&D effort, being a continuous R&D performer increases the duration of product innovation but it is not significant for the persistence in process innovation. This result confirms that, although in broad terms the R&D expenditure is determinant for the innovation output (Triguero and Córcoles, 2013), being persistent in R&D activities has a great influence on survival of product innovations but it is not decisive for the survival of process innovations (H2 is partially accepted). This result is in line with Parisi et al. (2006) which find that R&D intensity is positively and significantly associated with the introduction of product innovation but not with the probability of introducing a new process. One possible explanation could be, like these authors point out, that R&D has not a direct impact but an indirect effect on process innovation. That implies that R&D plays an important role in favoring the absorption of new more advanced technologies embodied in new investment goods.

In addition, the influence of previous experience in appropriability increases the persistence in product innovation but, surprising, reduces the survival in process

innovation. Nevertheless, given that the level of the parameter significance is low, the results should be taken cautiously in both cases. Thus, the hypothesis H3 cannot be accepted. One possible explanation could be that appropriability is likely to display a threshold effect, meaning that strengthening appropriability conditions will not necessarily determine further increases of rates of innovation (Dosi et al. 2006).

With respect to the influence of sustainability of exporting behavior on persistence in process and product innovation, a positive relationship is detected (significant coefficients at 99%-95% level in all specifications and negatively associated with the hazard rate). Consolidated firms in international markets (high probability of export survival) are able to better sustain their innovative strategies. Thus, the hypothesis H4 is accepted. This result is in line with previous studies which positively relate exports to innovation (Baldwin and Gu, 2004; Salomon and Myles Shaver, 2005; Cassiman et al., 2010). Nevertheless, these works analyze the influence of the exporting behavior in a specific year to explain the degree of persistence in innovation. Thus, learning outcomes from competition in international markets positively affects the capacity building of innovation.

Finally, differences in innovation persistence are confirmed depending on the industries in which firm operates. This result enables us to verify the hypothesis H5. Moreover, belonging to high-tech industries increases the probability of spell survival in product innovation whereas this condition is not a requisite for process innovation (H5a is confirmed). On the contrary, the fact of operating in a medium-tech sector reduces the probability of survival in product innovation but it is not significant for process innovation. Finally, coefficients for low-tech sectors are not significant for any type of innovation. This result indicates the difficulty to find in low-tech sectors different behaviors between persistence in product and process innovations (H5b is rejected).

With respect to the rest of control variables, there is a positive relationship between firm size and the ability to maintain process innovation. We do not find a significant influence of size on the persistence in product innovation. Thus, SME could achieve stable leader positions in product innovation.

Table 3. Estimation results for process and product innovation

	Clog-Log model* Discrete time Model with frailty (Exponential form)						Probit model Discrete time Model with frailty No proportional hazards (Marginal effects)					
	Process innovation			Product innovation			Process innovation			Product innovation		
	Model 7	Model 8	Model 9	model 10	model 11	Model 12	Model 13	Model 14	Model 15	Model 16	model 17	model 18
Previous spell duration	0.937*** (0.000)	0.938*** (0.000)	0.927*** (0.000)	0.951** (0.026)	0.954** (0.040)	0.943** (0.018)	-0.010*** (0.000)	-0.010*** (0.000)	-0.013*** (0.000)	-0.009* (0.054)	-0.008* (0.067)	-0.011** (0.020)
Number of previous spells	0.943* (0.092)	0.936* (0.057)	0.943 (0.129)	0.998 (0.957)	0.981 (0.682)	1.009 (0.862)	-0.011* (0.069)	-0.012** (0.041)	-0.012* (0.083)	-0.002 (0.796)	-0.006 (0.471)	-0.002 (0.848)
Survival of exports	0.694*** (0.007)	0.719** (0.016)	0.690** (0.014)	0.644*** (0.010)	0.648** (0.014)	0.638** (0.015)	-0.067*** (0.006)	-0.060** (0.014)	-0.070** (0.014)	-0.094** (0.013)	-0.085** (0.013)	-0.104*** (0.009)
Cumulative R&D/sales	1.130** (0.039)	0.704 (0.777)	1.146 (0.911)	0.011*** (0.002)	0.025** (0.023)	0.008*** (0.002)	0.060 (0.754)	-0.042 (0.840)	0.049 (0.834)	-0.824** (0.017)	-0.596** (0.048)	-0.981*** (0.002)
Registered patents	1.130** (0.039)	1.111* (0.073)	1.137* (0.051)	0.887* (0.082)	0.882* (0.075)	0.863** (0.045)	0.020** (0.048)	0.018* (0.082)	0.026** (0.036)	-0.018 (0.183)	-0.017 (0.176)	-0.021 (0.182)
Control variables												
High ^a	1.014 (0.834)		1.021 (0.775)	0.774*** (0.002)		0.747*** (0.001)	0.002 (0.889)		0.003 (0.853)	-0.046** (0.024)		-0.057*** (0.001)
Medium ^b	1.020 (0.699)		1.018 (0.763)	1.327*** (0.000)		1.379*** (0.000)	0.011 (0.723)		0.004 (0.741)	0.048*** (0.001)		0.064*** (0.000)
Low ^c	1.018 (0.743)		1.025 (0.693)	0.914 (0.172)		0.912 (0.219)	0.003 (0.743)		0.004 (0.714)	-0.016 (0.149)		-0.018 (0.246)
Sector dummies		yes			yes			Yes			yes	
Years in the current spell	0.798* (0.052)	0.783** (0.042)		0.821 (0.118)	0.844 (0.190)		-0.048*** (0.001)	-0.051*** (0.001)		-0.038 (0.457)	-0.055 (0.159)	
Size	0.875** (0.011)	0.874** (0.012)	0.872** (0.021)	1.173** (0.015)	1.083 (0.243)	1.194** (0.011)	-0.024*** (0.008)	-0.023** (0.011)	-0.026** (0.017)	0.031** (0.046)	0.013 (0.304)	0.038*** (0.009)
Constant	0.296*** (0.001)	0.274*** (0.001)	0.195*** (0.000)	0.291*** (0.000)	0.285*** (0.001)	0.202*** (0.000)						
Observations	9,485	9,485	9,429	7,539	7,509	7,539	9,485	9,485	9,485	7,539	7,509	7,539
Spells		3,633	3,689	2,855	2,825	2,855	3,689	3,633	3,689	2,855	2,825	2,855
Log likelihood	-4559.448	-4530.721	-4613.308	-3703.220	-3670.718	-3805.893	-4556.059	-4528.207	-4564.697	-3700.972	-3671.101	-3709.878

(^a)Reference: Medium and Low industries. (^b)Reference: High and Low industries (^c)Reference: High and

Medium industries. (*)Clog-log model has been estimated with the hshaz Stata command.

6. Conclusions

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

We confirm that 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 (significant and positive *lagged dependence* for product and process innovation). However, it is only accepted the significance of negative *occurrence dependence* for the process innovation, but not for product innovation.

These findings have implications for policy makers because the strategy choice in innovation may affect the persistence of their innovative activities. Firms that have only experience in process innovations have higher probability of ceasing innovation than firms that have past experience in product innovators. “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) depending on the type of innovation (process or product) strategy.

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 innovation in the current period but also enables firms to learn and face changes in exogenous factors. In particular, we have considered additional drivers related to learning capabilities of the firm such as the cumulative R&D effort, the potential appropriation of returns of innovation and the survival in foreign markets. Clog-log and probit models report similar results in the alternative specifications confirming the robustness of our results. We find some differences among the determinants of persistence in product and process innovation. First, previous experience is more conclusive for process than for product innovation. This result is consistent with previous empirical literature (Antonelli et al. 2012). Second, we confirm that being a continuous R&D performer increases the duration of product innovation but it is not significant for the persistence in process innovation. Third, we cannot confirm the positive influence of previous experience in appropriability on process innovation. The effect is only positive for maintaining the persistence in product innovation. Finally, a positive relationship is obtained between the survival of exports and the persistence in process and product innovations.

In sum, the past experience in product innovation gives a competitive “premium” over previous episodes of process innovation which reduces the risk of exit probability of ceasing innovation for Spanish manufacturing firms. In line with previous works results also suggest that persistence in product innovation is more intensive in high-tech industries which have much higher rates of introduction of new products (Clausen et. al, 2012). On the other hand, process innovation is more frequent and more persistent than product innovation in industries with a more homogeneous product (medium-tech industries). Product innovation is associated with high competitive markets and its persistence depends mostly on the sustainability of business strategies such as R&D effort and export persistence. Appropriability has a higher influence in persistence of product than in process innovation because patents are usually the protection mechanism used for product innovations and a lot of process innovations are not registered. In this regard, it is believed that lead times and learning curves are more effective ways for protecting process innovations than patents (Dosi, 1988) but this

issue needs further research. Process innovation is linked more closely to medium-tech sectors with less level of competitiveness. In spite of the positive influence of the opening of external markets, it is unclear the effect of other competitive strategies such as R&D expenditure or patents which may reduce the probability of survival in process innovation. Nevertheless, we can confirm that previous experience is less decisive for product innovation than process innovation and non-innovators can become product innovators without past experience in innovation.

References

Antonelli, C. 1997. The economics of path-dependence in industrial organization. *International Journal of Industrial Organization* 15, 643-675

Antonelli, C., Crespi, F. and Scellato, G., 2012a. Inside Innovation Persistence: New Evidence from Italian Micro-data, *Structural Change and Economic Dynamics* (in press DOI: 10.1016/j.strueco.2012.03.002).

Antonelli C., Crespi F. and Scellato G., 2012b. Internal And External Factors in Innovation Persistence, *Economics of Innovation and New Technology* (in press DOI:10.1080/10438599.2012.708135).

Audretsch (2003): Entrepreneurship: A survey of Literature, Enterprise Papers, 14, Enterprise Directorate-General, Brussels: European Commission.

Baldwin, J.R and Gu, W., 2004. Trade Liberalization: Export-market Participation, Productivity Growth, and Innovation. *Oxford Review of Economic Policy* 20(3), 372-392.

Becker, S. and Egger, P. H., 2013. Endogenous product versus process innovation and a firm's propensity to export. *Empirical Economics* 44(1), 329-354

Brenton, P., Saborowski, Ch. and von Uexkull, E., 2010. What Explains the Low Survival Rate of Developing Country Export Flows?. *The World Bank Economic Review* 24 (3), 474- 499.

Cabagnols, A. 2003. Technological Learning and Firm Persistence in Innovation: A France/UK Comparison Based on a Cox Model of Duration. Working Paper Centre Walras, University of Lyon 2.

Cabagnols, A. 2006. Comparing Innovative Persistence Across Countries: A Cox Model of Patenting in the UK and France. In: Le Bas, C. and Latham, W. (Eds.), *The Economics of Persistent Innovation: An Evolutionary View*. Economics of Science, Technology and Innovation, Volume 31, Springer, 119-165.

Cassiman, E., Golovko, E. and Martínez-Ros, E., 2010. Innovation, exports and productivity. *International Journal of Industrial* 28(4), 372–376.

Cefis, E., 2003. Is there Persistence in Innovative Activities? *International Journal of Industrial Organization* 21, 489-515.

Cefis, E. and Orsenigo, L., 2001. The persistence of innovative activities. A cross-countries and cross-sectors comparative analysis. *Research Policy* 30, 1139–1158.

- Clausen, T. H., Pohjola, M., Sapprasert, K. and B. Verspagen. 2012. Innovation Strategies as a Source of Persistent Innovation, *Industrial Corporate Change* 21 (3): 553-585.
- Cohen, W. and Levinthal, D. A., 1989. Innovation and Learning: The Two Faces of R&D – Implications for the Analysis of R&D Investment, *Economic Journal* 99, 569-96.
- Collier, W., 2005. Unemployment duration and individual heterogeneity: A regional study. *Applied Economics* 37, 133-153
- Cox, D.R. and Oakes, D., 1984. *Analysis of Survival Data*. London: Chapman and Hall.
- Doiron, D. and Gørgens, T.(2008). State dependence in youth labor market experiences and the evaluation of policy interventions. *Journal of Econometrics* 145, 81-97.
- Dosi, G., 1988. Sources, procedures, and microeconomic effects of innovation. *Journal of Economic Literature* 26(3), 1120-1171.
- Dosi, G., Marengo, L. and Pasquali, C., 2006. How much should society fuel the greed of innovators? On the relations between appropriability, opportunities and rates of innovation. *Research Policy* 35, 1110–1121
- Duguet, E. and Monjon, S., 2004. *Is Innovation Persistent at the Firm Level? An Econometric Examination Comparing the Propensity Score and Regression Methods*. Université Panthéon-Sorbonne (Paris 1)
- Flaig, G. and Stadler, M., 1994. Success breeds success. The dynamics of the innovation process. *Empirical Economics* 19, 55–68
- Fougère, D., Kramarz, F. and Magnac, T.2000. Youth employment policies in France. *European Economic Review* 44, 928-942
- Fritjers, P. 2002. The non-parametric identification of lagged duration dependence. *Economic letters* 75, 289-292
- Fugazza, M. and Molina, A.C., 2011. On the determinants of exports survival, FREIT Working Paper 311
- Geroski, P. A., Reenen, J. and Walters, C.F., 1997. How Persistently do Firms Innovate?. *Research Policy* 26, 33-48
- Heckman, J.J. and Singer, B., 1984. Econometric Duration Data. *Journal of Econometrics*, 24, 63-132
- Hess, W. and Persson, M., 2011a. The Duration of Trade Revisited. Continuous-Time vs. Discrete-Time Hazards. *Empirical Economics* (in press DOI: 10.1007/s00181-011-0518-4)
- Hess, W. and Persson, M., 2011b. Exploring the Duration of EU Imports. *Review of World Economics/ Weltwirtschaftliches Archiv* 147(4), 665-692.
- Huang, C.-H. and C.H. Yang. 2010. Persistence of innovation in Taiwan’s manufacturing firms. *Taiwan Economic Review* 38, no. 2: 199–231.
- Jang, S-L and Chen, J. H., 2011. What determines how long an innovative spell will last?. *Scientometrics* 86, 65–76

- Joyce, J.P., 2005. Time Past and Time Present: A Duration Analysis of IMF Program Spells. *Review of International Economics* 13(2), 283-297
- Kaplan, E. L. and Meier, P., 1958. Nonparametric estimation from incomplete observations. *Journal of the American Statistical Association* 53, 457-481
- Kiefer, N., 1988. Economic Duration Data and Hazard Functions. *Journal of Economic Literature* 26(2), 646-679
- Le Bas, C., Cabagnols, A. and C. Gay., 2003. *An evolutionary view on persistence in innovation: An empirical application of duration models*. In P. Saviotti (ed.) *Applied Evolutionary Economics: New Empirical Methods and Simulation Techniques*. INRA SERD, Pierre Mendès University, Grenoble and IDEFI-CNRS-UNSA Sophia-Antipolis, France.
- Le Bas, C, Mothe, C. and Nguyen-Thi, T. U., 2011. Technological innovation persistence: Literature survey and exploration of the role of organizational innovation. Working Paper 1132, GATE Groupe d'Analyse et de Théorie Économique Lyon-St Étienne
- Lelarge, C. 2006. Les entreprises industrielles françaises sont-elles à la frontière technologique? *Revue Economique* 57, 3: 473-484.
- Malerba, F. and Orsenigo, L., 1999. Technological Entry, Exit and Survival: an Empirical Analysis of Patent Data. *Research Policy* 28, 643-660
- Máñez-Castillejo, J. A.; Rochina-Barrachina, M. E.; Sanchis, A. and Sanchis, J. A., 2009. A Dynamic Approach to the Decision to Invest in R&D: The Role of Sunk Costs. *The Journal of Industrial Economics* 57, 712-735.
- Martínez-Ros, E. and Labeaga, J.M., 2009. Product and process innovation: persistence and complementarities. *European Management Review* 6(1), 64-75
- Obashi, A., 2010. Stability of Production Networks in East Asia: Duration and Survival of Trade. *Japan and the World Economy* 22(1), 21-30
- Parisi, M.L., Schiantarelli, F. and Sembenelli, A., 2006. Productivity, innovation and R&D: Micro evidence for Italy. *European Economic Review* 50, 2037-2061
- Peters, B., 2009. Persistence of Innovation: Stylised Facts and Panel Data Evidence. *The Journal of Technology Transfer* 34, 226-243
- Raymond, W., Mohnen, P.A., Palm, F. and Van der Loeff, S.S., 2010. Persistence of innovation in Dutch manufacturing: Is it spurious?. *The Review of Economics and Statistics* 92, 495-504
- Reichstein, T. and Salter, A. 2006. Investigating the sources of process innovation among UK manufacturing firms. *Industrial corporate Change*, 15, 653-682
- Rogers, M., 2004. Networks, Firm Size and Innovation. *Small Business Economics* 22(2), 141-153
- Roper, S. and Love, J. H., 2002. Innovation and export performance: evidence from the UK and German manufacturing plants. *Research Policy* 31(7), 1087-1102
- Salomon, R. and Myles Shaver, J., 2005. Learning by Exporting: New Insights from Examining Firm Innovation. *Journal of Economics & Management Strategy* 14(2), 431-460

Shao, J., Xu, K. and Qiu, B., 2012. Analysis of Chinese Manufacturing Export Duration. *China & World Economy* 20(4), 56-73.

Sueyoshi, G. T., 1995. A class of binary response models for grouped duration data. *Journal of Applied Econometrics* 10(4), 411–431.

Triguero, A. and Córcoles, D., 2013. Understanding innovation: An analysis of persistence for Spanish manufacturing firms. *Research Policy* 42 (2), 340–352

Van den Berg, G., 2001. Duration Models: Specification, Identification and Multiple Durations, *Handbook of Econometrics* 5, 3381-3460

Wooldridge, J.M., 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 20(1), 39–54

Appendix

Table A.1. Descriptive statistics: dependent variables

Variable	Definition	Observations (# firms)	Average	Std. error	Max	Min
Hazard rate of current spell of total innovation	Categorical variable indicating the discrete exit probability of a spell of total innovation (process, product innovation or both simultaneously). It is equals 1 when firm does not innovate in “ $t+1$ ” and it is equals zero in otherwise	16,123 (3,535)	0.240	0.427	1	0
Hazard rate of current spell of process innovation	Categorical variable indicating the discrete exit probability of a spell of process innovation It is equals 1 when firm does not innovate in “ $t+1$ ” and it is equals zero in otherwise	12,655 (3,161)	0.201	0.401	1	0
Hazard rate of product innovation	Categorical variable indicating the discrete exit probability of a spell of product innovation It is equals 1 when firm does not innovate in “ $t+1$ ” and it is equals zero in otherwise	9,243 (2,402)	0.2018	0.413	1	0

Source: Survey on Business Strategies (ESEE)

Table A.2. Explanatory and control variables

	Total innovation						Process innovation					Product innovation				
		Obs. (# firms)	Avg	Std. error	Max.	Min.	Obs. (# firms)	Avg	Std. error	Max.	Min.	Obs. (# firms)	Avg	Std. error	Max.	Min.
Explanatory variables																
Previous spell duration for process innovation	Duration of the previous spell of process innovation at the beginning of the current spell of total innovation	16,123 (3,535)	0.679	1.547	16	0										
Previous spell duration for product innovation	Duration of the previous spell of product innovation at the beginning of the current spell of total innovation	16,123 (3,535)	0.437	1.292	17	0										
Number of previous spells for process innovation	Number of previous spells of process innovation at the beginning of the current spell of total innovation	16,123 (3,535)	0.496	0.819	6	0										
Number of previous spells for product innovation	Number of previous spells of product innovation at the beginning of the current spell of total innovation	16,123 (3,535)	0.380	0.738	5	0										
Previous spell duration (process innovation)	Duration of the previous spell of process innovation at the beginning of the current spell of process innovation						12,655 (3,161)	1.013	1.903	17	0					
Previous spell duration (product innovation)	Duration of the previous spell of product innovation at the beginning of the current spell of product innovation											9,243 (2,402)	0.880	1.778	17	0
Number of previous spells (process innovation)	Number of the previous spells of process innovation at the beginning of the current spell of process innovation						12,655 (3,161)	0.601	0.879	6	0					
Number of previous	Number of the previous spells of											9,243 (2,402)	0.529	0.827	6	0

spells (product innovation)	product innovation at the beginning of the current spell of product innovation															
Industry classification according to technological degree.	Low technology industries=0 (OECD classification). This category includes: 1 Meat products; 2 Food and tobacco; 3 Beverage; 4 Textiles and clothing; 5 Leather, fur and footwear; 6 Timber; 7 Paper; 8 Printing; 19 Furniture; 20 Other manufacturing.	6,390 (1,593)	0.992	0.897	0	0	4,909 (1,377)	0.968	0.901	0	0	3,518 999	1.003	0.873	0	0
	Medium- Technology=1 (Low-Medium and High-medium OECD classification). This category includes: 10 Plastic and rubber products; 11 Nonmetal mineral products; 12 Basic metal products; 13 Fabricated metal products; 14 Machinery and equipment; 17 Vehicles and accessories; 18 Other transport equipment	6,519 (1,356)			1	1	5,306 (1,227)			1	1	3,489 925			1	1
	High technology industries=2 (OECD classification). This category includes: 9 Chemicals and pharmaceuticals; 15 Computer products, electronics and optical; 16 Electric	3,130 (593)			2	2	2,365 532			2	2	2,198 480			2	2

	materials and accessories															
Survival of exports	Survival rate of spell of export in the current year by firm	12,145 (2,472)	0.953	0.170	1	0	9,497 (2,206)	0.955	0.166	1	0	7,545 (1,819)	0.962	0.156	1	0
Cumulative R&D/sales	Accumulated R&D expenditures over sales from initial to current year	16,100 (3,529)	0.011	0.0232	0.617	0	12,637 (3,156)	0.011	0.022	0.617	0	9,227 (2,395)	0.014	0.026	0.617	0
Registered patents	Categorical variable Registerde patents=1 if the firm has registered any patent in <i>t</i> or in previous years	16,123 (3,535)	0.283	0.450	1	0	12,655 (3,161)	0.272	0.445	1	0	9,243 (2,402)	0.352	0.478	1	0
Control variables																
Id. Spell (total innov)	Control variable that uniquely identifies each spell of total innovation	16,123 (3,535)	2,652.537	1,616.880	5,807	1										
Id. Spell (process innovation)	Control variable that uniquely identifies each spell of process innovation						12,655 (3,161)	2,455.193	1,465.613	5,253	1					
Id. Spell (product innovation)	Control variable that uniquely identifies each spell of product innovation											9,243 (2,402)	1,753.901	1,053.162	3,726	1
Id. Seq (total innov)	Control variable that uniquely identifies each time period in the current spell of total innovation. For each spell Max: Id. Seq = duration of spell.	16,123 (3,535)	3.386	3.242	21	1										
Id. Seq (process innov)	Control variable that uniquely identifies each time period in the current spell of process innovation. For each spell Max: Id. Seq = duration of spell.						12,655 (3,161)	2.844	2.658	21	1					
Id. Seq (product innovation)	Control variable that uniquely identifies each time period in											9,243 (2,402)	3.092	2.984	21	1

	the current spell of product innovation. For each spell Max: Id. Seq = duration of spell.																
Years in the current spell of total innov.	Id.Seq for total innov in logarithms	16,123 (3,535)	0.868	0.809	3.045	0											
Years in the current spell of process innov.	Id.Seq for process innov in logarithms						12,655 (3,161)	0.733	0.748	3.045	0						
Years in the current spell of product innov.	Id.Seq for product innov in logarithms											9,243 (2,402)	0.786	0.788	3.045	0	
Size	Categorical variable which indicates firm size. Size=1 for medium-small firms (from 1 to 199 employees)	9,130 (2,592)	1.434	0.496	1	1	6,831 (2,246)	1.460	0.498	1	1	4,774 (1,586)	1.484	0.450	1	1	
	Size=2, 200 or more employees	6,993 (1,203)			2	2				5,824 (1,128)	2				2	4,469 (982)	2
Naceclio20	Categorical variable identifying the manufacturing sector for each firm. Values for Naceclio20 are: 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	16,039 (3,451)	10.633	5.448	20	1	12,580 (3,086)	10.581	5.404	20	1	9,205 (2,364)	10.919	5.558	20	1	

	Computer products, electronics and optical; 16 Electric materials and accessories; 17 Vehicles and accessories; 18 Other transport equipment; 19 Furniture; 20 Other manufacturing.																	
--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Source:ESEE