CÀTEDRA INNOVACIÓ EMPRESA

WORKING PAPERS

MEASURING THE PERSISTENCE IN INNOVATION IN SPANISH MANUFACTURING FIRMS: Empirical evidence using discrete-time duration models.

Angela Triguero[♥], David Córcoles and María C. Cuerva

University of Castilla-La Mancha (Spain)

Abstract

This paper measures the level of persistence in innovation using a large representative sample of Spanish manufacturing firms for the period 1990-2008. We determine the survival in innovation activities using discrete-time duration models controlling by some existing problems in continuous-time duration models used in the previous literature (unobserved heterogeneity and the proportional hazards assumption). This paper examines the relationship between the firm-specific characteristics of technological regimes and persistence measured by innovative spells at the firm level. Results show that high technological opportunities, patents and cumulativeness of learning based in previous experience and accumulated R&D as well as the use of generic knowledge provided by universities enhance the persistence in innovative activity.

Key words: persistence in innovation, discrete-time duration models, panel-data, technological regimes.

1. Introduction.

The persistence in innovative activities is an emerging area of interest in the empirical research of dynamics of technological change and firm's growth. The availability of new and large data sets has contributed to characterize the factors that determine the persistence of innovation at the firm level using patents, R&D or major innovations (Peters, 2009, Raymond et al., 2010, Antonelli et al., 2010 and Triguero and Córcoles, 2010 or Le Bas et al., 2011 for a survey). Nevertheless, most of these studies measure the degree of persistence in innovation considering proxies of innovative persistence instead of innovative spells by firms. This paper aims to help to shed light on the dynamism of innovation process measuring the degree of persistence in innovative activity at the level of individual firms. Hereafter, 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. As

[♥] Submitting author: Angela Triguero Cano. Facultad de Ciencias Económicas y Empresariales. Plaza de la Universidad, 1 02071. Albacete. Email: **Angela.Triguero@uclm.es**

far as we know, this is the first attempt to measure the innovation persistence using this methodology that solves some problems existing in the continuous-time duration models used in the previous studies (Geroski *et al*., 1997; Le Bas *et al*., 2003; Cabagnols, 2003; Jang and Chen, 2011).

Firm data on innovation and performance consistently show two main patterns of innovation in industries: creative destruction (Schumpeter Mark I) and creative accumulation (Schumpeter Mark II). Building upon this distinction, persistence is usually associated to a deepening pattern where knowledge accumulation contributes to a greater stability in the ranks of innovators (Malerba and Orsenigo, 1999). Empirical analysis provides considerable support to the hypothesis that the persistence at the sector level is related to the nature of the underlying technological regime (Malerba and Orsenigo, 1996; Breschi et al., 2000). However, the studies about persistence in innovation focused on how firm-specific conditions associated to particular technological regimes contribute to this phenomenon are still scarce. We consider that firm´s heterogeneity exists even within a sector. According to this idea, technological opportunity conditions, appropriability, cumulativeness of learning and nature of the knowledge base differ among industries but also contribute to enable firms to sustain their innovation more or less time within a particular technological regime. Hence, persistence depends also on the specific characteristics of technological regime where firm is operating.

The paper follows this outline. Section 2 reviews the empirical literature about persistence and technological regimes and purposes the reference conceptual model. Section 3 describes the data, innovation spells and the determinants of persistence in innovation. Section 4 presents the econometric methodology and summarizes the main results. Finally, Section 5 concludes.

2. Theoretical framework. The conceptual model: technological regimes and persistence in innovation.

One of the main findings in the innovation literature is that sector patterns of technical change are closely related to the nature of the underlying technological regime. Following Breschi et al. (2000), a technological regime can be broadly defined by the particular combination of four fundamental factors: technological opportunities, appropriability, cumulativeness of technological advances and properties of the knowledge base.

In general, Schumpeter Mark I industries (with a large and highly turbulent population of innovators) are related to high technological opportunities, low appropriability and low cumulativeness (at the firm level). In this framework, a limited role of generic knowledge leads to low concentration of innovative activities, high rates of entry and high instability in the hierarchy of innovators. On the other hand, Schumpeter Mark II (with a concentrated and rather stable population of innovators) is associated to low opportunity conditions, high appropriability and high cumulativeness and a generic knowledge base leading to a remarkable stability in the hierarchy of innovators[1]. From this perspective, persistence in innovation has been usually associated to a "deepening" pattern where knowledge accumulation contributes to a greater stability in the ranks of innovators (Malerba and Orsenigo, 1999). Empirical analyses provide considerable support to the hypothesis that the persistence is related to the nature of the underlying technological regime at the sector level. Technological regime described in terms of appropriability and opportunity conditions has been showed as a determinant factor of the concentration of innovation, stability in the ranking of innovators and the rate of technological entry in an industry (Nelson and Winter, 1982; Malerba and Orsenigo, 1996, 1999; Breschi et al., 2000). However, these studies do not focus on how firm-specific conditions associated to particular technological regimes contribute directly to persistence in the innovation activity. Since emphasis must shift to the relevance of the strategic behaviour of firms as the major determinant of industrial organization for linking innovation process to the dynamics of sectors (Dosi et al., 1994), we identify empirically how these firm-specific technological factors are influencing on the persistence in innovation at the micro-level.

Firstly, technological opportunities reflect the likelihood of innovating for any given amount of money invested in research by a firm (Cohen, 1995). Since firms are sensitive to the characteristics of the learning environment and technological regimes in which they operate, technological push will increase the probability of technological success. Thus, higher technological opportunities imply a higher persistence in innovation.

Appropriability is also necessary for generating and maintaining the rents stemming from leadership in technological activities (Levin et al., 1987). Appropriability conditions describe the degree to which an inventor can capture monopolistic rents from an innovation. Moreover, firms obtain early-mover learning advantages associated to innovative activity if exclusivity in the use of invention is guaranteed (Cohen, 1995). Despite a growing body of research there is no clear empirical consensus about whether higher appropriability encourages innovative activity at the firm-level. While greater spillovers (less appropriability) moderate the incentives to invest in R&D, there is an offsetting incentive to do R&D to absorb such technological spillovers (Cohen and Levinthal, 1989). However, the usefulness of such protection enables to capture the competitive advantages from R&D. Firms patent mainly for strategic reasons but not to appropriate directly returns from the patent (Cohen et al., 2000).

---

[1] Higher opportunities can favor the entry of new innovators reducing the stability in the ranking of innovators (measured by the rank correlation between the hierarchies of firms patenting in two different periods). However, high opportunity conditions in conjunction with high appropriability may also be associated to a Schumpeter Mark II pattern (Breschi et al. (2000, p. 394).

Being a persistent innovator is innovating continuously (without any or few interruptions in time). Since persistence implies that firm has to carry out a continuous effort to innovate and it depends on several factors (not only technological opportunities and appropriability conditions), we should consider the third dimension of technological regimes: cumulativeness. Cumulativeness is refereed to process resulting from knowledge accumulation formed by successive additions of previous firm's innovative experience. The empirical evidence about persistence in innovation provides a considerable amount of support to the "success breeds success" argument (Flaig and Stadler, 1994; Geroski et al., 1997). Furthermore, knowledge accumulation enhances the probability of future innovations and the persistence in innovative activities is led by the "learning by doing" effect (Peters, 2009). The previous experience should condition incentives to innovate and thus the likelihood and the persistence of innovation. This argument is straightforward but there is not enough conclusive empirical evidence to isolate the effect of previous firm's innovative experience on the persistence degree of innovative activities by firms.

Finally, the nature of the knowledge base must be considered. Properties of the knowledge have been also used to explain why the technological entry and exit, the concentration of innovative activities and the stability in the ranking of innovators differ at industry level helping to identify the Schumpeterian patterns of innovation (Breschi and Malerba, 1997). Knowledge base is close to basic sciences (generic knowledge) or applied sciences (specific knowledge) (Cohen and Levinthal, 1989; Breschi et al., 2000): Moreover, different degrees of specificity, tacitness (tacit or codified), complexity (simple or complex) and independence (independent or embedded in a system) of knowledge play a fundamental role in the innovation process (Winter, 1987). In this sense, an increasing importance of specific and more targeted knowledge (applied) tends to contribute to lower persistence in innovation respect to the use of basic knowledge (generic). This dynamics explains why a high importance of basic knowledge is a factor which increases the persistence in innovative activities.

3. Data and descriptive analysis

3.1. Data

The analysis is carried out at firm-level, covering the Spanish manufacturing industry over a period of 19 years, from 1990 to 2008. The data come from the Survey of Business Strategies (ESEE, *Encuesta sobre Estrategias Empresariales*) compiled by the Spanish Ministry of Science and Technology. The panel data is an unbalanced panel that includes all the manufacturing sectors. The coverage of the data set is mixed. A random sample is drawn for small companies (with less than 200 employees), keeping the sample representative of the industrial distribution, whereas the sample is complete for large firms (with more than 200 employees). Furthermore, new companies enter to the Survey each year to maintain the representativeness of the industry over the whole population (3252 firms).

3.2. Measuring the persistence: innovation spells

This paper focuses on innovation persistence. Unlike the traditional analyses which use as variable if the firm has introduced process/product innovation or patents, conduct R&D or several innovation measures, our dependent variable is the innovation spell. For each firm, we identify whether an innovation is introduced in a given year and how long innovative activity is continued without interruption. Therefore, our interest is turned towards the length of time a firm is continuously innovating. For instance, if firm *i* started to innovate in 1991 and ceased to innovate in 1995, the innovation process is regarding as having a spell duration of 4 years.

The methodology to construct our dependent variable is easy. Given the random sample of innovative manufacturing firms, we calculate the number of consecutive years of innovation for each one. Therefore, a spell is defined as the number of years firms innovate without interruption. Each spell will have the duration of *T* years. We have to take into account that in many cases there is no information about the whole duration of the spell. The reason could be either the firm still innovates in the last observation year (right-censuring) or the moment in which the firm begins innovating is unknown (left-censuring). In both cases, it is observed that $T>t$. That means that the length of the innovation period is larger than the observed one.

The main aim of the empirical studies of duration data is to analyze the exit probability of the spell in the year *t* (to stop innovation), conditioned by having remained in this spell at least *t* years. This conditional probability is known as "hazard rate" and in continuous terms as "hazard function". Following Kiefer´s notation the probability distribution of the innovation duration is defined as:

$$F(t)= Pr(T<t) \quad (1)$$

This equation specifies the probability that a spell lasts less than any value of *t*. In our case, $t= 1, 2, \ldots 19$ since our sample contains 19 years from 1990 to 2008. The corresponding density function would be:

$$F(t)=dF(t)/dt \quad (2)$$

In this type of analysis, it is also defined the "survival function" as the inverse of the accumulated distribution that means:

$$S(t)= 1-F(t)=Pr(T\geq t) \quad (3)$$

The interpretation of $S(t)$ is the probability of a spell lasts equal or more than the period of time under consideration. Additionally, the hazard rate is defined as the probability of a firm stops being innovator in the moment *t*, conditioned to the firm has not finished the innovation activity before *t*.

$$\emptyset(t) = \Pr(T = t \| T \geq t) = \frac{\Pr(T = t)}{\Pr(T \geq t)} \tag{4}$$

The hazard rate depends on the spell length, as long as its value changes with *t*. In this sense, a negative dependence between *t* and the hazard rate indicates innovation persistence across time. If we have a sample of spells of different durations arranged according to the duration from the smallest to the largest one, we can calculate the shape of the hazard function using a non-parametric estimation and survival functions by the Kaplan-Meier (1958) estimation. These estimations control by right-censoring problem but not by left-censoring problem.

We define n_t as the number of observations with a duration of at least *t* years. In other words, n_t is the number of firms which continue being innovators in the period *t.* The sample includes both complete and censoring observations. On the other hand, we define h_t as the number of observations which finish exactly in *t*, or in other words, the number of spells with duration of t years. In this way, the exit rate (hazard) can be estimated by the following form:

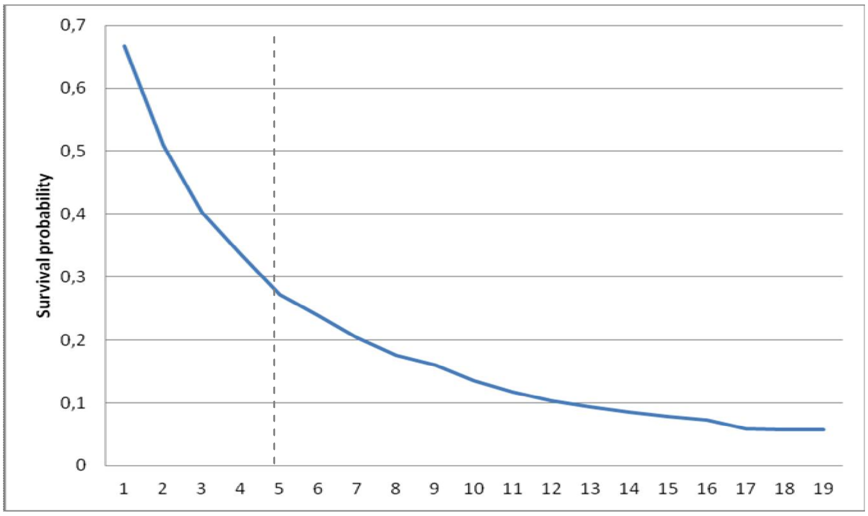
$$\emptyset(t) = \Pr(T = t | T \geq t) = \frac{\Pr(T = t)}{\Pr(T \geq t)} = \frac{h_t}{n_t} \tag{5}$$

and, from this result, the survival function is determined by the expression:

$$S(t) = \prod_{t=1}^{t} 1 - \emptyset(t) = \prod_{t=1}^{t} \left(1 - \frac{h_t}{n_t}\right) \tag{6}$$

Figure 2 reports the Survival curves. The results for all the observed spells during the period 1990-2008 confirm the low degree of survival of firms in terms of innovation in the early 5-6 years. During these first years, the decrease in the survival rate is sharp but afterwards the survival rates slowly decline. The downward and decreasing slope of the function shows that the probability of survival decreases as long as the duration of the spells increases. Additionally, the more the firms innovate, the less the survival rate decreases. At the end of the period, only around 5% of the innovative firms existing at the beginning of the period continue innovating. These results lead to the conclusion that persistence in innovation is low during the early years, but after 6-7 years the survival rates remain nearly constant.

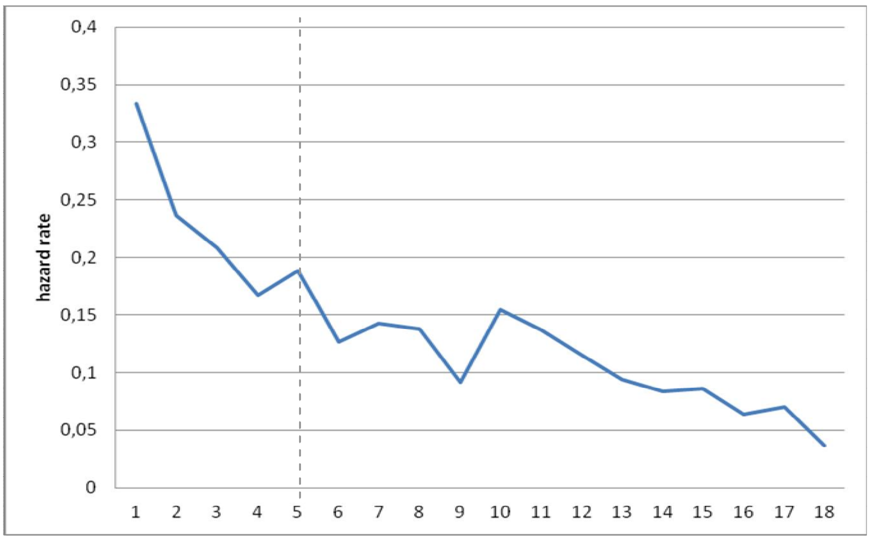
Figure 2. Survival function of innovation



Source: ESEE

Alternatively, in terms of hazard rates (exit rate of spell), the probability of interrupting the innovative activity is higher in the early 5-6 years, but then decreases once the innovation activity lasts for a certain period of time (Figure 3). For instance, the hazard rate in the year 18 (2007) is below 4%.This characteristic then implies a threshold above which all firms that survive have a higher probability to be persistent. Despite most firms are occasional innovators, they are more likely to survive if this threshold is surpassed.

Figure 3. Hazard function of innovation



Source: ESEE

Table 1 completes the descriptive previous analysis. In the first two columns we present the results for the complete sample of spells. While the probability of survival at least one year is more than 67%, this probability decreases up to 13.5% in the 10th year. In the case of the hazard rate, a substantial portion of the innovation activity decreases within the early years, especially in the first year when the probability of exit of the spell is around 33%. Meanwhile, this probability falls to 15% in the 10th year. The high number of spells confirms that the behaviour of the firms is very irregular in terms of innovation, contributing to explain the low degree of persistence in innovation. On average, firms innovate less than 3 consecutive years (2.7 years).

Following Obashi (2010), Table 1 also presents additional estimations to test the robustness of the results. With this purpose, we firstly eliminate the spells in which we do not know the beginning year. That implies to remove all spells beginnig in the first year, because there is no information on whether innovation activity started exactly in 1990 or in some previous year, and those ones that are preceded by a missing value in the previous year. Doing that, we take into account the left-censoring problem. Secondly, we try to solve the potential measurement error problem. In this case, the modified sample assumes that information failures are more feasible when the innovative activity is interrupted only one year and is continuing the following year. In those cases, the original spells (the two spells before and after the gap) are linked with the aim of treat them as a single longer spell (1-year-gap-adjusted sample)[2]. For instance, if a innovative firm states that the first year innovates, the second year there is no information and in the third year the firm confirms again to innovate, instead of considering 2 spells of one-year lenght, we assume a measurement error in the second year and suppose that this intermediate year the firm has continued innovating. In this case, we would consider only one spell of three-year lenght.

The new two estimations only change marginally the survival and hazard rates, but they do not alter the previous conclusions obtained with the complete sample of spells. Our results are robust. The risk that the innovation activity stops is higher in the first years but the probability of exit decreases across time. Low persistence in innovation seems to be a characteristic of Spanish firms, specially in the early 5-6 years.

[2] We have only considered measurement error in the case that the gap between two spells is a missing value. We have not taken into account the cero values (no innovation) with the aim of being the most restricted as possible and do not alter considerably survey responses.

Table 1. Spells and hazard and survival functions. Descriptive analysis

	All spells		Without left-censoring		1-year- gap-adjusted	
	Survival	Hazard	Survival	Hazard	Survival	Hazard
1	0.667	0.333	0.634	0.366	0.666	0.334
2	0.509	0.236	0.477	0.247	0.508	0.236
10	0.135	0.155	0.107	0.185	0.134	0.152
18	0.057	0.037	0.041		0.057	0.037
Num. spells	5290		3460		5259	
Average num. spells by firm	1.627		1.634		1.617	
Average spell duration	2.746		2.568		2.768	
Num. Firms	3252		2117		3252	
Num. Observations	14527		8887		14558	

Source: ESEE

3.3. The determinants of hazard rates

Following the theoretical background, we consider four dimensions of technological regimes that are likely to affect persistence in innovation: technological opportunities, appropriability conditions, accumulativeness and the nature of knowledge base (see Table A.1 in the Appendix).

Technological opportunities assess the ease of innovation in a particular sector. These opportunities are usually measured at industry level. Opportunity has been proxied by industry dummies representing differences across industries (Scherer 1982; Levin et al. 1987) or taking into account industry differences in R&D intensity (Levin et al. 1985, Cohen et al. 1987, Cohen and Levinthal 1989). These approaches are mainly associated to the opportunity of specific innovations under particular industry-level conditions. A categorical variable is considered based on OECD taxonomy on manufacturing industries' distinguishing industries by their technological intensity[3]. Huang and Yang (2010) used a comparable measure for controlling by the technological environment. They characterized the subgroups of scientific and non-scientific industries to examine the persistence of innovation in Taiwan's manufacturing sector during the period 1990-2003. The phenomenon of innovation persistence is found stronger in scientific industries compared to non-scientific industries. Hence, technological opportunities affect continuity in the performance of innovations.

[3] High and medium-high-technology industries include Chemicals, Machinery and Equipment, Office, Accounting and computing machinery, Electrical machinery and apparatus, Motor vehicles, Railroad equipment and transport equipment n.e.c. and Low and medium-low technology industries include Food, beverages and tobacco, Textiles, leather and footwear, Wood, paper, printing and publishing, Rubber and plastic products, Other non-metallic mineral products, Basic metals and fabricated metal products, and manufacturing n.e.c.

In relation to the measurement of appropriability of innovation, we consider that patents establish ownership rights protecting innovators against imitators. To proxy this variable, we use a dummy that takes the value 1 if firm has registered any patent in the current year. The main argument is that the innovative advantages decrease by the losses generated by reduced appropriability. Thus, low appropriability must reduce the probability of persistence in innovation. Although persistence studies using patent data are numerous (Cefis and Orsenigo, 2001, Cefis, 2003, Geroski et al., 1997) the individual effect of appropriability on persistence has not often considered[4]. Le Bas et al. (2011) consider two variables on appropriability conditions: strategic protection and formal protection. The first indicator considers the importance of strategic methods (secrecy, complexity of design, lead-time advantage over competitors). The second is equivalent to our measure and includes patents, trademarks, registration or copyrights. They found that appropriability conditions (supported by formal protection) 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.

Cumulativeness is measured through three indicators: the duration of the previous spell, the number of previous spells and the accumulated R&D. The first indicator measures the relationship between the length of the innovative spell and the length of its previous innovative spell (a relationship which reflects something like an innovation learning curve in the sense of Geroski et al., 1997). The larger the successive years that firms innovate continuously in the past, the higher the persistence in innovation must be in the actual period ("success breeds success"). Secondly, the number of previous spells captures the level of pre-spell innovative activity in terms of entry and exit rates in different spells. In this case, the relationship between this indicator and the persistence is negative because a high number of previous spells means that the firm has ended and started innovation more times ("failure breeds failure"). Finally, the existence of sunk costs associated to R&D spending justifies the inclusion of accumulated R&D until the current period. In this sense, we have to remember that cumulativeness means that technological capabilities in the present are the basis for future innovations and their existence encourages to the firm to adopt a persistent innovation strategy.

Finally, we consider the properties of the firm´s knowledge base considering the proximity to either *basic* science or *applied* science. We assume that *basic* or *generic* science is associated with broad research usually developed by universities and research institutes. In the same way, *applied* science refers to specific knowledge generated within the industry itself through research within the company group, suppliers, competitors, customers and consultants. Raymond et al., (2010) and Le Bas et al., (2011) also control for the proximity to science according to the importance of the sources of information stemming from institutional research. Although some empirical studies have not found benefits of

---

[4] Patents measure the persistence of innovative leadership rather than of innovation behavior because not all inventions are patented (Duguet and Monjon, 2004).

generated knowledge sourced from universities (Veugelers and Cassiman, 2005), we consider that this type of cooperation partner contributes to the persistence of innovative activity.

Additionally, we control by the firm size measured as the number of employees. Although this size effect has been showed higher in manufacturing than in services (Peters, 2009) and in product innovations than in process innovations (Clausen et al., 2011), the existing literature has generally highlighted the presence of a positive relationship between firm size and persistence in innovation (Cohen and Levin, 1989; Triguero and Córcoles, 2010; Huang and Yang, 2010). The number of years in the current spell is also considered among control variables. In addition, we introduce sector dummies as proxies for technological opportunity variables in alternative specifications to explain inter-industry variation in technological opportunities (Cohen and Levin, 1989).

4. Methodology and results

4.1. Econometric methodology

In this paper we model the determinant factors of persistence in innovation by the estimation of duration models. Although this methodolgy has been often used in labour economics, it has been extended to others economic fields in the last years[5]. In relation to innovation, the previos studies applying this methodology has usually taken into account the duration of patents (Geroski *et al*., 1997; Le Bas *et al*., 2003; Cabagnols, 2003; Jang and Chen, 2011).

The basic idea of the survival models is that from the definition of innovation spell is possible to analyze the influence of several factors on the duration (persistence) of innovation activities. Therefore, the general specification of our model is:

$$\phi(t) = f(X) \qquad (7)$$

where *X* is a vector of determinant factors including: the previous spell duration, the number of previous spells, the cumulative R&D expenditures, the technological opportunities, the patent activity, the use of basic research and other control dummies such as years of the current spell or size.

The parameters of the model measure the impact of these explanatory variables in the exit probability of the spell ($\phi(t)$). In other words, the dependent variable is the hazard function. Therefore, a

[5] See Collier (2005) for the field of labor economics and Obashi (2010) and Hess and Persson (2011b) in international economics.

negative value of the attached coefficient to the explanatory variable indicates a higher probability of spell length (a higher persistence in innovation).

The empirical literature that analyzes persistence in innovation from duration models has used two types of different methodologies: a semi-parametric Cox proportional hazards model (Cabagnols, 2003) or Weilbull duration models (Geroski *et al*., 1997; Le Bas *et al.,* 2003; Jang and Chen, 2011). Nevertheless, recent studies highlight some reasons that justify why this kind of models may be inappropriate when it comes to analyzing the determinant factors of duration (Brenton *et al.,* 2010; b, 2010, 2011; Fugazza and Molina, 2011)[6]. First, both of them -Cox and Weilbull models- assume that duration data are continuous. However, innovation data are referred to discrete-time intervals (years). Moreover, the non-continuity of the innovative activities leads to numerous short length spells which entail many tied survival times (Hess and Persson, 2011b). In this case, the continuous-time models may result in biased coefficients and standard errors. For this reason is more suitable the use of discrete-time duration models (Cox and Oakes, 1984). Second, Cox models do not control by the unobserved heterogeneity (or frailty) what could be a problem, especially in panel data with a large number of firms as well as a long period of time. In this sense, results could not only be biased, but also be spurious. Finally, continuous-time models, especially the Cox model, assume proportional hazards understanding that the effects of the determinant factors on different moments of spell duration are proportional.

The use of discrete-time models solves these three problems (Hess y Persson, 2011a) since a) they do not have difficulties with the ties, b) the unobserved heterogeneity can be easily controlled and c) it is even possible to relax assumption about the proportional hazards. Taken into account these properties, a continuous-time model (Cox) and two discrete-time models (clog-log model and probit model) are estimated. The clog-log and probit models have advantages over the Cox model because both of them control for the unobserved heterogeneity: the probit model assumes a normal function for the frailty distribution and the clog-log model determines frailty with a more flexible functional form by mass points (Heckman and Singer, 1984). Moreover, an additional advantage of probit model is that it does not imply to assume proportional hazards (Sueyoshi, 1995).

Furthermore, we present three different specifications for each model. The first considers our measure of technological opportunities conditions based on OECD taxonomy distinguishing between high and low technology industries. In the second one, we control by technological opportunities introducing sector dummies. Finally, the number of "years in the current spell" is omitted in the third specification[7].

---

[6] These papers are referred to external trade relationships, but their conclusions about the advantages of this methodology could be easily extrapolated to the duration analysis of innovation.

[7] Since the introduction of this variable is not possible in a model type Cox, we only report the two first specifications.

Additionally, we have re-estimated the clog-log model considering two alternative samples: a sample without left-censoring problems and a sample taking into account potential measurement error (1-year-gap-adjusted sample) (Table 3). The aim is to test the robustness of the alternative methods.

4.2. Results

The empirical results are presented in Table 2 for each of the methodologies explained in the previous section. The final sample has 14474 observations and 5280 spells. The sign of the coefficients does not change in any of them and their level of significance is quite similar. In addition, the log likelihood values are highly similar in all the specifications. Therefore, we can assume that we obtain consistent results in all the specifications. The corresponding p-values are reported in parentheses.

We first consider the relevance of cumulativeness measured by the previous spell duration, the number of previous spells and the level of accumulated R&D. Results confirm the influence of previous experience (cumulativeness) on the probability of survival in innovation. Based upon the regression results, the estimated coefficients of previous spell duration and cumulative R&D level have a positive (negatively) effect on survival (hazard) in innovation. It indicates that a longer previous spell in the past increases the probability of persistence in the present. Similarly, we find a negative relation between the probability of exit of the innovation spell and the "cumulative R&D" variable. The firms accumulating more efforts in R&D are also more prone to consolidate their innovation position in the future due to the existence of sunk costs associate to R&D expenditure. Although the Cox model does not offer conclusive results for this R&D accumulation (no significant coefficient), the clog-log and the probit models confirm a negative correlation at the 99% level of significance. These results confirm the role of knowledge accumulation because the probability to introduce further innovations in the future is affected by the previous capabilities of each firm to accumulate and exploit technological knowledge (Antonelli and Scellato, 2009). The importance of cumulativeness is reinforced if we pay attention to the variable referring to the number of previous spells. In this case, a high number of previous spells indicates a non-persistent innovative behaviour in the past. Firms that have a high number of previous spells are less persistent because they often change their innovation strategy and are not able to accumulate knowledge as persistent innovators.

Table 2. Estimation results

	Cox Model Continuous time		**Clog-Log model*** Discrete time Model with frailty			**Probit model** Discrete time Model with frailty No proportional hazards		
	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 7
Cumulativeness								
Previous spell duration	-0.034*** (0.004)	-0.034*** (0.005)	-0.036*** (0.006)	-0.037*** (0.006)	-0.043*** (0.006)	-0.025*** (0.002)	-0.024*** (0.003)	-0.032*** (0.001)
Number of previous spells	0.084*** (0.000)	0.082*** (0.001)	0.085*** (0.001)	0.085*** (0.002)	0.116*** (0.000)	0.061*** (0.001)	0.057*** (0.002)	0.077*** (0.001)
Cumulative R&D	-0.347	-0.325	-6.09***	-6.014***	-6.839***	-2.952***	-2.840***	-3.787***

	(0.197)	(0.228)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technological opportunities								
Low	0.193*** (0.000)		0.164*** (0.000)		0.209*** (0.000)	0.116*** (0.000)		0.151*** (0.000)
Appropriability conditions								
Having patents	-0.036** (0.039)	-0.035** (0.045)	-0.294*** (0.000)	-0.292*** (0.000)	-0.328*** (0.000)	-0.183*** (0.000)	-0.174*** (0.000)	-0.213*** (0.000)
Properties of knowledge base								
Ocasional basic research	-0.230*** (0.000)	-0.228*** (0.000)	-0.205*** (0.000)	-0.209*** (0.000)	-0.256*** (0.000)	-0.144*** (0.000)	-0.142*** (0.000)	-0.181*** (0.000)
Frequent basic research	-0.380*** (0.000)	-0.395*** (0.000)	-0.334*** (0.000)	-0.362*** (0.000)	-0.433*** (0.000)	-0.209*** (0.000)	-0.221*** (0.000)	-0.265*** (0.000)
Control variables								
Years in the current spell			-0.312*** (0.000)	-0.283*** (0.003)		-0.207*** (0.001)	-0.219*** (0.000)	
Size	-0.055*** (0.000)	-0.055*** (0.000)	-0.422*** (0.000)	-0.423*** (0.000)	-0.488*** (0.000)	-0.282*** (0.000)	-0.275*** (0.000)	-0.344*** (0.000)
Sector dummy		yes		yes			yes	
Constant			-0.748*** (0.000)	-1.117*** (0.000)	-1.290*** (0.000)	-0.251*** (0.000)	-0.472*** (0.000)	-0.267*** (0.000)
Observations	14474	14474	14474	14474	14474	14474	14474	14474
Spells	5280	5280	5280	5280	5280	5280	5280	5280
Log likelihood	-27368.019	-27351.100	-7513.783	-7492.975	-7519.543	-7520.721	-7499.085	-7536.235

*Clog-log model has been estimated using the *hshaz* Stata command.

Technological opportunities are also decisive for the level of innovation persistence. In particular, firms belonging to low- tech industries tend to have a lower probability of survival in the spell than firms in high-tech industries. In line with Huang and Yang (2010), we find a positive and significant coefficient at the 99% level of significance.

With regard to the appropriability, patents show a significant influence on the persistence in innovative activities, indicating that the existence of adequate appropriation mechanism decreases the hazard probability. This result is also confirmed by Le Bas et al. (2011). Finally, turning to the relevance of particular sources of technological knowledge, *basic* research is a positive determinant factor for increasing the innovation persistence. Firms using information from universities or research institutes increase (decrease) the probability of survival (exit) in the spell. An "occasional" or "frequent" basic research influences negatively and significantly in the three models. These negative signs suggest that a generic technological base proxied by particular sources of technological knowledge (publicly funded research made in universities and research institutes) enhances the persistence degree in the innovation process. This external source of information appears to play a major role in shaping the survival of the firm. This finding coincides with the positive relationship found by Raymond et al. (2010) between proximity to science sources and persistence. Le Bas et al. (2011) also found a direct relationship between science sources and occasional innovators. Finally, we point out the negative sign of the "years in the current spell" variable, confirming the negative relation between the hazard rate and the length of the spell. This result is consistent with the obtained in section 3.2 in the univariate analysis about hazard and survival functions. Additionally, we find a negative relation between the hazard rate and the firm size that suggests that the largest firms are more persistent in innovation.

Table 3 reports the clog-log model results for the two alternative samples (without left- censuring problem and 1-year-gap-adjusted) to check the robustness of the results. In broad terms, results are quite similar to those ones obtained in Table 2. The two samples show similar signs from the original estimation and the significance levels remains.

Table 3. Robustness check. Alternative samples for Clog-log model*.

	Total Spells			No left-censoring			One-year-gap-adjusted		
	model 3	model 4	model 5	model 9	model 10	model 11	model 12	model 13	model 14
Cumulativeness									
Previous spell duration	-0.036***	-0.037***	-0.043***	-0.044**	-0.044**	-0.053***	-0.037***	-0.037***	-0.043***
	(0.006)	(0.006)	(0.006)	(0.010)	(0.013)	(0.009)	(0.005)	(0.006)	(0.005)
Number of previous spells	0.085***	0.085***	0.116***	0.047	0.045	0.073*	0.088***	0.088***	0.122***
	(0.001)	(0.002)	(0.000)	(0.149)	(0.184)	(0.057)	(0.001)	(0.001)	(0.000)
Cumulative R&D	-6.09***	-6.014***	-6.839***	-5.221***	-5.053***	-5.675***	-6.016***	-5.948***	-6.803***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Technological opportunities									
Low	0.164***		0.209***	0.143***		0.182***	0.162***		0.205***
	(0.000)		(0.000)	(0.001)		(0.005)	(0.000)		(0.000)
Appropriability conditions									
Having patents	-0.294***	-0.292***	-0.328***	-0.265***	-0.264***	-0.311***	-0.294***	-0.292***	-0.328***
	(0.000)	(0.000)	(0.000)	(0.005)	(0.006)	(0.002)	(0.000)	(0.000)	(0.000)
Properties of knowledge base									
Occasional basic research	-0.205***	-0.209***	-0.256***	-0.179***	-0.200***	-0.234***	-0.204***	-0.208***	-0.257***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Frequent basic research	-0.334***	-0.362***	-0.433***	-0.326***	-0.363***	-0.431***	-0.331***	-0.357***	-0.435***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables									
Years in the current spell	-0.312***	-0.283***		-0.312***	-0.261***		-0.323***	-0.295***	
	(0.000)	(0.003)		(0.003)	(0.007)		(0.000)	(0.002)	
Size	-0.422***	-0.423***	-0.488***	-0.423***	-0.431***	-0.470***	-0.416***	-0.416***	-0.483***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sector dummy		yes			yes			yes	
Constant	-0.748***	-1.117***	-1.290***	-0.672***	-0.918***	-1.186***	-0.734***	-1.103***	-1.300***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	14474	14474	14474	8859	8859	8859	14774	14774	14774
Spells	5280	5280	5280	3451	3451	3451	5249	5249	5249
Log. Likelihood	-7513.783	-7492.975	-7519.543	-4860.186	-4844.871	-4864.681	-7511.528	-7490.786	-7517.652

*Clog-log model has been estimated using the *hshaz* Stata command.

5. Conclusions

This paper examines the persistence in innovation at the firm level in the Spanish manufacturing industry during the period 1990-2008. Persistence is measured by the number of successive years in which a firm innovates (innovation spells) instead to consider proxies of innovative persistence as in previous studies. Moreover, an univariate analysis is made based in non-parametric techniques and the probability that the spell will end at any particular time (the hazard rate) is modelled in a multivariate framework.

The univariate analysis of innovation spells shows a low survival degree of innovation in the early years and the highest values of hazard rates. Only around 30% of firms continue innovating after five years. The average value of spell duration is below three years. However we find a negative relation between hazard rates and spell duration, indicating persistence of innovation especially in periods larger than 5-6 years. This result suggests that the innovation is especially stable after some years of cumulative knowledge. There exists a threshold above which all firms that survive have a high probability to be persistent.

As regards the multivariate analysis, a contribution of this paper is the use of discrete-time duration models to measure the determinant factors of survival in innovation. As far as we know, this is the first attempt to measure the persistence innovation using a methodology that solves some problems existing in the continuous-time duration models used in previous studies (Geroski *et al*., 1997; Le Bas *et al*., 2003; Cabagnols, 2003; Jang and Chen, 2011). Based upon alternative methodologies and specifications (continuous and discrete-time), the econometric results confirm that technological opportunities, patents and cumulativeness of learning based in previous experience and accumulated R&D as well as the use of generic knowledge provided by universities enhance the persistence degree in the innovation process.

In broad terms, econometric results find a strength and positive relation between the previous experience (cumulativeness) and the probability of survival in innovation. Both the previous spell duration and cumulative R&D expenses decrease the probability of stopping the innovation in the firm. Additionally, a non-persistent innovative behaviour in the past (high number of previous and short spells), has a negative (positively) effect on survival (hazard).

Technological opportunities at sector level also enhance the probability of survival. In high-tech sectors, firms are more prone to continue their innovative activity across time. These results provide more evidence about inter-industry differences in the innovation process. Furthermore, the debate about what must be the role of public R&D funding in different sectors in a context of public and private financial constraints could be opened.

Cumulativeness, technological opportunities and appropriability are not enough to explain survival suggesting that external sources of information must be considered. We also find a positive relation between persistence of innovation and the collaboration with universities and research centres as a proxy of properties of knowledge base. As argued by Le Bas et al. (2011), the importance of organizational innovation in the study of persistence should be considered. Although empirical studies have started to explore this topic more work needs to be done in this direction including the recent phenomenon of open innovation (Chesbrough, 2003). Finally, econometric results confirm the persistence of innovation (negative relation between stopping innovation and length of spell) and a positive relation between size and the survival rate. The robustness of these results is confirmed with repeated estimations taken into account the left-censured problem and the 1-year-gap spells.

Our results confirm that persistence depends positively on high technological opportunities, appropriability and cumulativeness and generic nature of knowledge base (measured by the acquisition of external knowledge in the universities and research institutes) as well as the size and the length of years in the innovation spell. Our interpretation of these results is that persistence in innovation exists in firms belonging to the two Schumpeterian regimes: Mark I and Mark II. Although more persistence is usually found in the "deepening" pattern of innovation, it has been showed that the probability that the spell will end falls the longer it goes (negative duration dependence). However, there exists a threshold above which the firms that have continuously innovating have less probability to stop innovating. "*If at first you don't succeed, try, try again*".

6. References.

Antonelli, C., Crespi, F. and Scellato, G., 2010. Inside Innovation Persistence: New Evidence from Italian Micro-data, Collegio Carlo Alberto, Working paper No. 10/2010.

Antonelli, C. and Scellato G., 2009. The persistence of Innovation: the Italian Evidence, University of Torino, Department of Economics, Research Paper No. 3/2009.

Breschi, S. and Malerba, F., 1997. Sectoral Innovation Systems: Technological Regimes, Schumpeterian Dynamics, and Spatial Boundaries. In: Edquist, C. (Ed.), Systems of Innovation: Technologies, Institution and Organisations Pinter, London, Washington.

Breschi, S., Malerba, F. and Orsenigo, L., 2000. Schumpeterian Patterns of Innovation and Technological Regimes. *The Economic Journal* 110, 388-410.

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

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.

Chesbrough, H.W., 2003. Open Innovation: The New Imperative for Creating and Profiting from Technology. Harvard Business School Press, Boston MA.

Clausen, T. Pohjola, M., Sapprasert, K. and Verspagen, B., 2011. Innovation strategies as a source of persistent innovation. *Industrial and Corporate Change,* first published online September 2, doi:10.1093/icc/dtr051

Cohen, W., 1995. Empirical studies of innovative activity, In P. Stoneman (Ed.): Handbook of the Economics of Innovation and Technological Change, Oxford: Basil Blackwell, 182-264.

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.

Cohen, W. and Levin, R.C., 1989. Empirical Studies of Innovation and Market Structure, en R. Schmalensee y R. Willing (Ed.): *Handbook of Industrial Organization*, vol. 2, 1059-1107. Amsterdam. Elsevier.

Cohen, W., Levin, R. C and Mowery, D., 1987. Firm Size and R&D Intensity: A Re-examination. *Journal of Industrial Economics*, 35, 543-63.

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.

Cohen, W., Nelson, R. R. and Walsh, J. P., 2000. Protecting their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or not). NBER working paper No. 7552.

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.

Dosi, G., Malerba, F. and Orsenigo, L., 1994. Evolutionary Regimes and Industrial Dynamics Evolutionary and Neo-Schumpeterian Approaches to Economics. Recent Economic Thought Series, Volume 36, II, 203-229.

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.

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*, 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 (2), 199–231.

Jang, S-L and Chen, J. H., 2011. What determines how long an innovative spell will last?, *Scientometrics* 86, 65–76.

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-Thi1, T.U., 2011. Technological innovation persistence: Literature survey and exploration of the role of organizational innovation, CEPS/INSTEAD, Working Paper No 2011-54.

Levin, R. C., Cohen, W. M. and Mowery, D. C., 1985. R&D appropriability, opportunity, and market structure: New evidence on some Schumpeterian hypotheses. *The American Economic Review*, 75, 20–24.

Levin, R.R., Klevorick, A.K., Nelson, R.R. and Winter, S.G., 1987. Appropriating the returns from industrial R&D. *Brooking Papers on Economic Activity* 3, 783–820.

Malerba, F. and Orsenigo, L., 1996. Schumpeterian patterns of innovation are technology-specific. *Research Policy* 25, 451–478.

Malerba, F. and Orsenigo, L., 1999. Technological Entry, Exit and Survival: an Empirical Analysis of Patent Data. *Research Policy* 28, 643-660.

Nelson, R. R. and Winter, S.G., 1982. An Evolutionary Theory of Economic Change. Cambridge, Mass.: Harvard University Press**.**

Obashi, A., 2010. Stability of Production Networks in East Asia: Duration and Survival of Trade, *Japan and the World Economy*, 22(1), 21-30.

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.

Scherer, F. M., 1982. Demand-pull and Technological Opportunity: Scmookler Revisited. *Journal of Industrial Economics*, 30, 225-37.

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., 2010. Understanding the innovation: An analysis of persistence for Spanish manufacturing firms. Paper presented at the 12th Annual Conference ETSG, 9–11 September 2010, Lausanne.

Veugelers, R., and Cassiman, B., 2005. R&D Cooperation between Firms and Universities. Some Empirical Evidence form Belgian Manufacturing, *International Journal of Industrial Organisation*, 23, 355-379.

Winter, S., 1987. Knowledge and competencies as strategic assets. In: Teece, D. (Ed.), The Competitive Challenge. Ballinger, Cambridge.

Table A.1. Descriptive statistics: explanatory variables.

		Number of observations (# firms)		Average values		Standard error	
Variable	**Definition**	**Whole sample**	***Innovators***	**Whole sample**	***Innovators***	**Whole sample**	***Innovators***
Previous spell duration	Duration of the previous spell corresponding to the firm i	14527 (3252)	14527 (3252)	5.667	5.667	4.652	4.652
Number of previous spells	*Number of the previous innovative spells* corresponding to the firm i	14527 (3252)	14527 (3252)	0.517	0.517	0.802	0.802
Accumulated R&D	Accumulated R&D expenditures over sales from initial to current year	61319 (4617)	14504 (3216)	0.007	0.011	0.023	0.011
Technologies opportunities	Low and medium-low technology industries =1	64098 (3435)	9234 (2284)	0.271	0.364	0.445	0.481
	High and medium-high-technology industries=0	23853 (1332)	5293 (1040)				
Having patents	Categorical variable Having patents=1 if the firm register any patent in the current year.	34798 (4627)	14497 (3252)	0.066	0.116	0.248	0.320
Occasional basic research*	Categorical variable which indicates whether the company collaborated with universities and/or technological parks four or less years	14345 (755)	3639 (387)	0.176	0.327	0.381	0.469
Frequent basic research*	Categorical variable which indicates whether the company collaborated with universities and/or technological parks five or more years	6365 (335)	3417 (330)	0.086	0.313	0.281	0.464
Years in the current spell	Years of current innovation spell (in logarithms)	14527 (3252)	14527 (3252)	0.856	0.856	0.804	0.804
Size	Categorical variable which indicates firm size. Size=1 for medium-smalls firms (from 1 to 199 employees) and Size=0 200 or more employees	87951 (4629)	14527 (3252)	0.726	0.443	0.446	0.497

* "Non-basic research" as a reference value in average values. Source: ESEE.