Innovation, growth and survival of Spanish manufacturing firms

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Abstract:

This paper empirically analyzes the relationship between innovation, growth and survival at the firm level. Firm survival is usually considered as the best single indicator of firm performance. The analysis is carried out applying survival methods to a representative sample of Spanish manufacturing firms over the period 1995-2010. The data are drawn from the Encuesta Sobre Estrategias Empresariales (ESEE). This paper deepens into the understanding of the selection mechanism at work in markets that drives out unfitted-to-survive firms. The results point out that previous growth and innovative effort of the firms are important drivers of this process that substantially reduce the risk of failure of firms.

Keywords: survival, innovation, firm's growth

JEL classification: F12, L25, C25.

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1. Introduction

The aim of this work is to shed some light on the relationship between innovation, growth and survival at the firm level, providing new evidence coming from a representative sample of Spanish manufacturing firms.

In particular, we try to better understand the functioning of the selection mechanism operated by the market, looking at the relevance of past growth rates in explaining the firms' survival. The significance of past growth in explaining survival rates differences among firms may be taken as the sign of an effective short-run mechanism of selection of the most efficient firms which gain over less efficient counterparts in terms of market shares. Conversely, if past growth rates result to be not significant in explaining survival rates differences, market selection may operate *via* the elimination (exit) of the less efficient firms in the medium/long-run, without being so effective in re-distributing market shares in a year-to-year basis. The effect of past growth rate on survival likelihood is analyzed once firm size differences are controlled for. Firm size is not only a key variable in explaining heterogeneity in the adoption of business strategies among firms, but it has also a well-known impact on survival rates.

Moreover, together with past growth rates, we explore the role played by the innovative effort of the firms and their survival chances. In doing so, we try to exploit the different dimensions that characterize the innovation process; both at the investment and output levels, also taking into account its inherent nature of complexity and uncertainty. The hypothesis is that innovation processes positively affect to firm survival by increasing the set of available resources and increasing firm's ability to succeed in increasingly competitive markets.

Previous studies have mainly focused on the study of the first few years of life of a cohort of newly born firms to draw conclusions on post-entry performance. A shortcoming of this approach is that the robustness of the empirical results heavily rests on how representative the particular cohort examined is. In this line, Audretsch (1991) argues that the determinants of new entrants' survival crucially depend on the length of the period in which survival is measured; furthermore, Wagner (1994) underlines the desirability of analyzing several cohorts, given that the particular year may be relevant in explaining the distinctive life patterns of these firms. Finally, the entry opportunities and survival chances of new firms may also depend on how incumbents react and adapt to the new competitive environment, i.e. they may not be independent on how the market conducts its selection process among entrants and incumbents.

In this study we examine the survival patterns of a representative sample of Spanish manufacturing firms, including both newly created firms and incumbents, over the period from 1995 to 2010. This constitutes a major difference from the majority of studies conducted before, which only have used a subset of entrants in a particular year, following them over a short period of time. The sample under analysis has been drawn from the *Encuesta sobre Estrategias Empresariales* (ESEE, henceforth), a survey carried out annually since 1990. It comprises 3326 firms, for which their entry date is known, that are followed until 2010. Of them, 403 failed. The ESEE also provides rich information at the firm level that is used to explain the determinants of the risk of firm failure.

The contribution of this work is twofold. First, we deepen the understanding of the functioning of the selection mechanism operated by the market, looking at the relevance of past growth rates in explaining the survival probability of firms. We find that low-growth firms face a higher risk of exit, while both fast-growth firms and moderate upsizers and downsizers face do not differ much in terms of their survival prospects. Second, we further explore the different dimensions of the innovation process and how they do affect firms' survival, taking into account its inherent nature of complexity and uncertainty. Firms' Innovative (input and output) activities protect them from failure.

The paper is organized as follows. Section 2 presents a brief revision of the related literature. In Section 3 both the data and methods are described. Section 4 is devoted to discuss the empirical results, and Section 5 concludes.

2. Literature review

2.1 Theoretical background

This paper explores the relationship between firm innovation, growth and survival. In fact, growth and survival of firms should be considered as fairly related phenomena. On the one hand, growth may be though as being the channel through which market selection operates in the short-run via a reallocation of market shares to the most efficient firms; on the other hand, firms' survival may be the result of a (medium) long-run process of selection of firms, where either firms exhibit "acceptable" performance as time passes, or they lose the major part of their profits, finally exiting the market. The relationship between firms' growth and survival may be shaped by industry-specific characteristics, mostly related to the nature of dominant technology in the industry. From a static point of view, scale economies are relevant: industries characterized by large economies of scale should show higher post entry growth rates (of survivors), because firms which do not grow should suffer the most --in terms of cost inefficiencies -- for the gap between current size and the minimum efficient scale (MES). In a dynamic perspective, the very "nature" of innovation should be taken into account: both growth and survival may depend on the ability in changing strategies as the environment changes. All in all, growing and continuing to operate in the market by new firms should be, *ceteris paribus*, a tougher achievement in more turbulent markets (i.e., those characterized by the rapid emergence of new ideas, linked to a faster emergence of new products and processes; see Geroski, 1995).

Different theoretical developments have placed emphasis on different mechanisms that shape the relationship among innovation, growth and survival. Dynamic (neoclassical) competitive models underline the role of firms' efficiency and the effectiveness of market selection in shaping firms' growth and survival. For example, in Jovanovic's (1982) model of passive learning, surviving younger (and smaller) firms, characterized by a time invariant efficiency parameter, grow more than older (and larger) counterparts: this is the result of a market selection process, i.e. the *between-firm effect*, which brings to the growth of the most efficient firms and –as time passes-- the shrink and the exit of the least efficient ones (see Jovanovic, 1982, p. 656). In the Ericson and Pakes (1995) active learning framework, firms decide in each period whether to exit or to operate in the market, and in the second case, the level of exploratory investments in order to rationally maximize expected profits: higher levels of investment ensure more favorable distribution of the efficiency levels in the next period (see Pakes and Ericson, 1998, p. 17 and p.19).

Conversely, the evolutionary tradition places more emphasis on the idiosyncratic characteristics of the firm (and not just on the competitive market selection mechanism), which has to be understood as the implementation of different organizational setups, processes of production and attitude to innovate at the level of the firm. Heterogeneous firms are characterized by different learning processes that make them improving their efficiency, i.e. the *within-firm effect*. Selection among different variants of technology, equipment and lines of production occurs to a good extent within firms (see Coad, 2007; Bottazzi et al., 2010; Dosi, 2012 pp. 23-26, among others), mainly driven by the implementation of better processes of production (process innovation) or the introduction of new products (product innovation). Following the evolutionary tradition, the short-run market selection mechanism via reallocation of market shares is not so effective in real markets[1], while a long-run selection is still at work, operating through the elimination (exit) of the worst and obsolete performers.

Summing up, different traditions in the rich literature on industrial dynamics claim for a complex (and not unique) structure of the "mechanics" linking learning, competition, growth and survival. Each of these strands of the literature stresses either more one channel or another, mainly differentiating themselves between those which claim for a major role played by the market selection mechanism (in the short-run) among incumbent firms, i.e. the *between effect*, and those which claim for a selection mechanism operated (in the medium/long-run) at the level of the firm through the implementation of better products and processes, i.e. the *within effect*.

Holding on one approach or the other, it is possible to suggest different structures of the relationship between innovation, growth and survival, which may be captured with the empirical exercise conducted in this paper. In particular, if short-run market selection was effective, we should expect a stronger association between past growth rates and survival probabilities on the yearly or multi-yearly time scale: more efficient firms should first gain market shares, which should in turn be reflected in higher survival rates; if market selection was not effective, diverse degrees of efficiencies and innovation among firms should yield to relevant profitability differences, which in turn, should affect survival rates. Hence, one would expect a rather loose relationship between growth and survival.

[1] With this respect, some differences among economic systems should be underlined. In the U.S., the between (re-allocation) effect seems to be relevant in explaining the labor productivity (LP) and total factor productivity (TFP) change. For example, Baily, Hulten and Campbell (1992) and Haltiwanger (1997) find that reallocation of market shares explain the 50% of TFP growth in the U.S. manufacturing sector in the period which goes from the beginning of the seventies to the end of the eighties, and, in a much recent work, Bartelsman, Haltiwanger, Scarpetta (2009) claim that in the U.S. the covariance term of the productivity growth decomposition –which refers to reallocation-- is higher than in the considered EU countries (UK, Germany, France, Netherlands, Hungary, Romania) in the 1990s. Conversely, the evidence for EU does not claim for a strong between effect: Arnold, Nicoletti and Scarpetta (2008) which perform a cross-country analysis of TFP growth in the early 2000s in UK, Italy, France and Spain, show that just the 20-40% of TFP growth is explained by reallocation of market shares to the most productive firms, even with huge cross-country heterogeneity.

The innovation process may also definitely affect the probability of surviving: *process innovation* may play a role in enhancing firms' efficiency (lowering costs), and *product innovation* may be seen as an alternative strategy taken by firms in order to build market niches, assuring better profit margins, thus bringing to a path in which firms do not need necessarily to grow in order to survive.

Overall, theoretical contributions do not say a final word on the prevailing mechanism at work in the relationship between innovation, growth and survival and the challenge becomes empirical: in the last years a significant amount of research on the topic has flourished.

2.2 Some results in previous empirical studies

The research devoted to examine the role played by innovation in shaping firms' growth and survival rates can be split into two groups. Firstly, those studies that mainly focus on the industry-level characteristics related to the emergence of new products and processes (for example the speed of diffusion and the nature of technology adopted in the industry). Secondly, those studies analyzing the effect of the propensity to innovate (i.e. the number of products and processes introduced) by single firms over their growth rates and survival probabilities.

Among the first group of studies, Audretsch (1995) analyzes 11,322 new-firm entrants in U.S. manufacturing in 1976 and their patterns of growth and survival until 1986. The author finds that *surviving* new entrants show higher growth rates than incumbent firms in highly innovative industries: this is due to the process of learning about the viability of the new product subsequent to entering, which in these industries needs to be fast; those firms which find that the new product is viable in the market will grow, while those for which that is not the case will exit. Considering all new entrants, survival rates in highly innovative industries will be lower than those in less innovative industries (Audretsch, 1995; p. 450). Cefis and Marsili (2005), using a sample of manufacturing firms in the Netherlands from 1996 to 2003, find that in non-science based industries, (both product and process) innovations introduced by the firm have a significant positive effect on the probability to survive, while that seems not to be true in science-based industries, suggesting that in these sectors innovation must be coupled with firm-specific capabilities to generate a premium in survival. Interestingly enough, these authors also find that in science-based industries the most important variable for surviving is the past growth rate which has a strong positive effect on firm survival (Cefis and Marsili, 2005; p. 1182).

When one comes to analyze the role of firm innovation on its probability to survive, new insights arise. Cefis and Marsili (2006), again analyzing a sample of Dutch enterprises in 1996, find that innovation premium in terms of survival rates may be particularly high for small and young firms. Helmers and Rogers (2010), analyzing the behavior of 162,000 limited companies in Britain from 2001 to 2005, find a systematic negative effect of patenting and trademarking on the probability to exit, which seems to be also related to the sector in which the firm is active.

These studies do not really exploit much the complex nature of the innovation process. Unlike them, Buddelmeyer et al. (2010) try to account for different degrees of uncertainty in the innovation process, trying to measure the different dimensions of it. Coad and Rao (2008) take a similar perspective, even if they look at the effect of innovation on firms' growth rates: they find that innovation has a positive and strong effect in terms of sales growth of fast-growing firms, while it has even a negative effect for those firms which shrink during the analyzed period of time. The explanation may lie in the very nature of innovation: "[I]t may be that innovation actually does lead to a decline in sales in a minority of cases, because of the inherent uncertainty of innovative activity" (see Coad and Rao, 2008; p.644).

3. Data and methods

3.1 Data

The data used in this paper are drawn from the ESEE Survey for the period 1995-2010. The ESEE is an annual survey of Spanish manufacturing firms sponsored by the Ministry of Industry and carried out since 1990.[2] It is an unbalanced panel of firms that excludes manufacturing firms with less than 10 employees, while firms with 10 to 200 employees (SMEs henceforth) are randomly sampled by industry (20 two-digits NACE rev.2 industries –see Appendix 1) and size strata (4 groups). Firms larger than 200 employees are surveyed exhaustively, resulting in a response rate of approximately 60% of the population.[3] The survey provides information on the date of entry to the market (date of birth) and to the survey (when a firm first comes under observation). Besides, the survey allows identifying whether a firm stays in business, exits or leaves the survey.[4]

[2] The survey started in 1990, but we analyze the period 1995 onwards in order to avoid changes in the questionnaire in initial years.
[3] Important efforts have been made to minimize attrition and annually incorporate new firms with same sample criteria as in the base year to maintain the representativeness of the sample over time (see http://funep.es for further details.
[4] Note that the ESEE is not a mandatory survey.

Table 1. Descriptive statistics

	All firms	SMEs	Large
Number of observations	21,171	14,959	6,212
Number of firms	3,326	2,462	864
Exits (closures)	403	321	82
Firm characteristics:[1]			
Annual employment growth (%)	0.2	0.0	0.7
% of firms with increase in employment	41.1	38.2	48.4
% of firms with constant employment	13.9	18.8	1.9
% of firms with decrease in employment	45.0	43.0	49.7
Labour productivity (euros per hour)	84.1	68.9	120.7
% of exporters	64.3	52.5	93.1
Age (number of years)	29.0	24.5	39.9
% of familiar firms	42.4	54.2	14.2
% of firms with R&D expenses	36.4	21.8	71.5
% of firms with foreign ownership	19.7	9.3	44.7
R&D over total sales (all firms) (%)	0.7	0.5	1.2
R&D over total sales (firms with positive expenses) (%)	2.0	2.3	1.7
Operating surplus over sales (%)	9.0	8.5	9.5

[1] The figures correspond to non-weighted averages across all observations.

The empirical analysis is carried out for firms existing in the panel dataset over the period 1995-2010. These firms constitute a representative sample of the population, including both new firms and incumbents. A firm is computed to year *t* when this is the last year of the firm in the market. That is, the firm is in the market in year *t* but no longer in operation in *t+1*. Exit includes permanent closure, firm in liquidation and shift to non-manufacturing activities. In practice, the most common exit mode is bankruptcy. We do not consider as exit (failure) when a firm mergers with or is acquired by another one. The latter firms, those leaving the survey and those firms still alive at the end of the sample period are right-censored observations, that is, we know that in the last period that we have information on them it did not end in failure. This is easily handled by the empirical methodology. Given our definition of exit, information in 2010 is only used to identify those firms exiting in 2009.

The ESEE is well suited to pursue firm-level analysis since it provides rich information on firm characteristics and strategic choices (innovative activities, advertising, internationalization,…). However, the nature of the survey imposes some limitations to carry out survival analysis. If we pursue a traditional approach based on *firm age*, that is firm spells from birth to death, we would face a problem due to the existence of left-truncated spells. That is, even accepting that the sample is representative of existing manufacturing firms, short-lived spells would be unrepresented leading a problem of biased estimates.[5] The alternative we follow in this study is to carry out an analysis based on *calendar time*, where the focus lies on explaining the determinants

[5] Esteve-Pérez and Máñez (2008) carry out an analysis based on firms' age after accounting for left-truncation.

of the hazard of exit at particular year given that the sample of firms is representative of the population of manufacturing firms (further details in the methodology section below). In this case, we will obtain unbiased estimates of the determinants of the hazard rate.

The sample (top panel of Table 1) is made up of a total of 21171 observations, corresponding to 3326 firms, with 403 of them exiting (12.12% of firms). The panel of firms is unbalanced due to entry and exit of firms from both the market and the survey. Besides, columns (2) and (3) provide information for SMEs (10-200 employees) and large firms (200+ employees). This is interesting given the different sampling procedure for these two groups. Thus, the sample comprises 14959 observations for SMEs, corresponding to 2462 firms, and 6212 observations for large firms, corresponding to 864 firms. At first glance, the incidence of failure is higher for SMEs.

3.2 Estimation method

The empirical analysis is carried out using survival methods, which are appropriate to analyse the determinants of firm exit.[6] These methods take into account the evolution of the risk of failure and its determinants over time since they control for both the occurrence and the timing of exit. Furthermore, survival methods are suitable in the presence of right censoring, when we only know that the firm has survived at least up to a given period *t*, and easily handle time-varying covariates. The latter is a desirable property since a firm's ability to survive varies over time as the competitive environment in the market changes (Mata et al., 1995).

The central concept in survival analysis is the *hazard rat*e. Following Kalbfleisch and Prentice (1980), the *hazard rat*e is defined as the probability that a firm exits the market in a moment *t* conditional upon survival up to that time *t*, and conditional on a vector of covariates *X*, which may include both time-variant and time-invariant explanatory variables,

$$\lambda\left(t;X\right)=\lim_{dt\to 0}\frac{\Pr\left[t\le T<t+dt\setminus T\ge t,X\right]}{dt}, \qquad (1)$$

where *T* is a non-negative random variable (duration), which is assumed to be continuous. Hence, $\lambda(t)$ is an instantaneous exit rate.

In order to examine the determinants of firm survival, we analyze the effect of a set of explanatory variables, *X*, on the exit rates. We use two different methodologies. First, we carry out (non-parametric) log-rank tests of equality of hazard functions across the *r*-groups in which firms are classified according to the *r-values* of each covariate (Cleves et al. 2004). The log-rank test is an extension of non-parametric rank tests comparing two or more distributions for censored data. Under the null hypothesis, there is no difference in the hazard rate of each of the *r* groups at any of the exit times and the t-statistic distributes as χ^2 with *r-1* degrees of freedom.

[6] See Kiefer (1988) for an overview of the application of these methods to economic studies.

Secondly, we carry out a multivariate analysis of exit estimating semi-parametric Cox Proportional Hazards models (CPHM, henceforth) proposed by Cox (1972, 1975). Therefore, we estimate the following model:

$$\lambda(t) = \lambda_0(t)\exp(X'\beta) \qquad (2)$$

where $\lambda_0(t)$ is an unspecified *baseline function* obtained for all values of the covariates equal to zero (X=0) , and β is a vector of unknown parameters. In this specification, the effect of the independent variables is a parallel shift of the baseline function, which is estimated for all those firms that survive up to a particular period.

Parameters are consistently estimated rather than by maximum likelihood by the partial likelihood method of estimation (Cox, 1975), which does not depend on the baseline function. Partial likelihood works in terms of the ordering of events and conditional probability. Let T_1..., T_N be N possibly right-censored exit times and X_1..., X_N be the corresponding explanatory variables vector where X_i is observed on [0, T_i]. Therefore, the maximum partial likelihood estimator, $\hat{\beta}$, is the value that maximizes the partial likelihood function

$$L(\beta) = \prod_{i=1}^{N}\left[\frac{\exp\left(X_i^{'}(T_i)\beta\right)}{\sum_{j\in R_i}\exp\left\{X_j^{'}(T_i)\beta\right\}}\right]^{c_i} \qquad (3)$$

where R_i is the set of firms at risk of exit (that is, still alive) at time T_i, and c_i is an indicator variable that takes value 1 if T_i is an observed failure time and value 0 otherwise. The CPHM considers that survival time is a continuous variable so that firms may be ordered exactly with respect to their exit time. However, since we analyse yearly data, we use the method proposed by Efron (1977) for handling "ties" (i.e., firms suffering the event *k* during the same period).

A desirable feature of the CPHM that makes it suitable for our analysis is that it is only the ordering of exit times what matters for the estimation, and not the actual times by themselves. The particular time of exit is only important to control who is compared to whom. This is an important characteristic since our analysis is based on calendar time. Hence, as calendar time changes, the risk of suffering the event of failure/ liquidation/acquisition also changes. In our model, the baseline hazard function controls for the overall evolution of risk common to all firms in the market in a particular year, independently of the age of the firm, such as the risk related to macroeconomic conditions. Thus, firm age is to be included as an explanatory variable.[7]

[7] The presence of left censored observations, i.e. firms that started production some time before the beginning of the sample period, is not a problem in this case given that the interest lies on the study of the conditional probability of exit and the date of birth is known. Moreover, the problem of left-truncation is also overcome given that the dataset comprises a representative of the population of Spanish manufacturing firms with ten or more employees in each period.

3.3 Explanatory variables

In this section, we outline firm and industry characteristics used as explanatory variables in the empirical model (i.e. X covariates).

a) Firm size and growth

For firm *Size* we use an employment measure. It is calculated as the average number of employees across the year.[8] This variable is used to calculate year-to-year growth rate of a firm.

To distinguish across different growth regimes, we have calculated a discrete variable with three groups according to percentiles of the distribution of firms' growth in a certain period in its corresponding two-digit industry. High-growth firms are those with employment growth above the 75th percentile; low-growth firms are those whose growth was below the 25th percentile. Thus, medium-growth firms are those with employment growth between the 25th and 75th percentiles. In the regression analysis, we define 3 dummy variables (*Growth1*; *Growth2* and *Growth3*) capturing these growth regimes.

b) Firm innovative activities

Firms' innovative activity is proxied using both input and output measures of the technological effort. As for the input measure of innovative effort, we use two variables: (i) a dummy variable (R&D) that takes value one if the firm performs R&D activities, and zero otherwise; (ii) the ratio of R&D expenses to sales (*Tech_effort*). Related to the latter variable, we create a discrete variable splitting firms into three groups according to the values of the distribution of this variable in a certain period in its industry. In contrast to the firm-growth variable, in this case the large accumulation in zero (i.e., no R&D expenses) leads us to implement a different procedure. The three states are defined according to whether the firm did not invest in R&D, it invested with low intensity (below the median of its industry in that year), or with high intensity (above the 50th percentile). In the regression analysis, we define 3 dummy variables capturing this classification. Finally,we also use output measures of innovation. Two dummy variables are defined and take value one when the firm declares to introduce product (*Inn_Product*) of process (*Inn-Process*) innovations.

c) Control variables

A set of control variables is also included in the empirical analysis. First, firm age is calculated as the difference between the current calendar year *t* and the year of birth reported by the firm. A dummy variable (*Age*) splits firms into young (i.e. firms five years old or younger) and old firms.

Second, three dummy variables capturing export activity (*Export*), family owned firms (*Family*) and foreign ownership (*Foreign*) are also included in the analysis. With respect to exports, there is a vast empirical literature (see, for example, Bernard et al., 2007) that indicates the superior

[8] Specifically, it is the addition of two types of employees. On the one hand, the average number of temporary employees in each quarter is used if they vary considerably throughout the year. If not, then the number of temporary employees at the end of the year is used. On the other hand, the equivalent number of permanent employees, including weighted part-time employees. Again, when the number of permanent employees has changed significantly throughout the year, the average number across the four quarters is used.

performance of exporters with respect to non-exporters, even when industries are narrowly defined. With respect to family owned firms, different authors have suggested a non-linear effect of family owned firms on survival likelihood. That non-linearity would be driven by the retirement of the founder, which could opt for closing down the business if there are no viable conditions for the persistence of family control after her retirement (Lotti and Santarelli, 2005). This dummy variable takes value 1 if owners have managerial responsibilities in the firm, and 0 otherwise. Finally, *Foreign* variable also takes value 1 if there is foreign participation in firm's ownership.

Third, two performance variables are also included in the empirical analysis. On the one hand, *Labour Productivity* is calculated as the ratio between production and the number of effective hours worked. Production value is deflated with individual (firm level) output deflators, which is rather unusual information that we are able to work out from information on price variation provided by firms. On the other hand, an indicator of profitability is included (*Margin*), which is calculated as operating surplus over sales. This variable is defined as the value of gross output minus variable costs of production divided by the value of total sales. The gross output value is computed as total sales, plus stock variation and other revenues, while variable costs of production include intermediate consumption (raw materials and services) and labour costs. We create discrete variables to split firms into three groups according to their values in the distribution of firms' productivity in a certain period in its corresponding two-digit industry (25^{th} and 75^{th} percentiles). Hence, in the regression analysis we create three dummy variables for each variable in order to capture these classifications (*Productivity1*; *Productivity2; Productivity3; Margin1; Margin2; Margin3*).

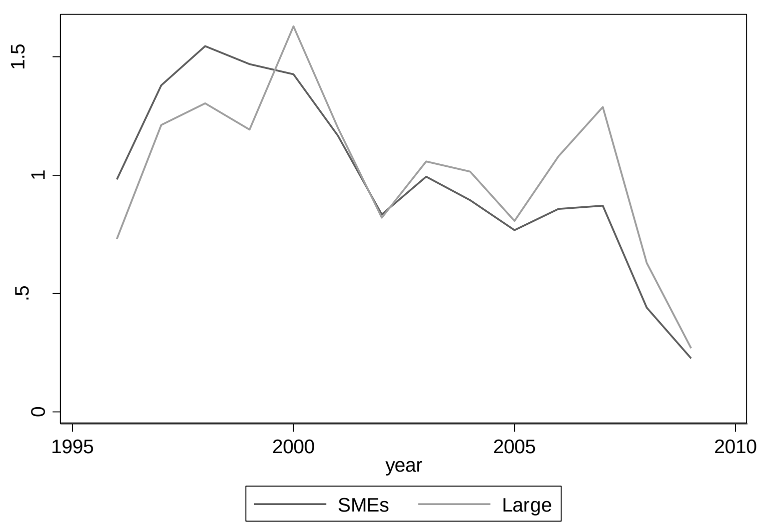
Finally, we also account for the technological intensity of the industry in which firms operate. It may shape the effect of firms' innovative activity on their survival prospects. We proceed by aggregating initial manufacturing industries according to two different classifications. Firstly, we collapse the twenty initial industries into four broader groups following the criterion applied by Eurostat to elaborate the Statistics on high-tech industry and knowledge-intensive sectors. This consists on the aggregation of the manufacturing industries according to technological intensity (R&D expenditure/value added) and it is based on the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2) at the 2-digit level. The four groups are the following: 1(Low), 2 (Medium-Low), 3(Medium-high) and 4(High) technological intensity of the industry. In the regression analysis, four dummy variables are included to capture them (Tech_level1-Tech_level4). Secondly, we use an aggregation of Knowledge Intensive Activities (*KIA*), which is also used in the high-tech statistics previously referred. It is based on the share of tertiary educated people in each sector of industries and services according to NACE at 2-digit level for all EU 27 Member States. In practice, only two sectors (Manufacture of pharmaceutical products and manufacture of computer, electronic and optical products) are considered as Knowledge Intensive Activities (KIA). The third one (Manufacture of coke and refined petroleum products) is the only manufacturing industry not covered by the ESEE.

Table 1 shows some descriptive statistics on the explanatory variables. Overall, there is remarkable heterogeneity across firms. Employment growth is higher for large firms. This is consistent with a larger percentage of firms with positive increases for this group of firms.

Although this result could be to some extent unexpected (for instance, Klette et al., 2004), two considerations are in order. First, the likelihood of observing a firm without variation in employment between two consecutive years is much higher for SMEs than for their large counterparts. Second, the comparison between groups of firms with positive and negative employment growth shows differences in relative performance of SMEs and large firms throughout the sample period. Figure 1 shows the yearly ratio of both percentages; i.e. percentage of firms with increase versus with decrease in employment. As can be seen, the superior performance for larger firms is basically due to relative better employment performance than SMEs in last years.

The average values for the rest of explanatory variables are as expected. Large firm are more productive and older, while they are less commonly family-owned businesses and are more participated by foreign capital. Additionally, they export and are engaged in R&D activities more frequently than SMEs. However, as happens when some business strategies once we control for differences in sizes, technological effort is larger for small and medium enterprises that carry out R&D. Finally, operating profits are, on average, smaller for SMEs.

Figure 1. Ratio of firms with increase in employment over firms with decrease in employment



4. Descriptive analysis and estimation results

Figure 2 displays a non-parametric estimate of the hazard rate, that is, the probability that a firm exits the market through liquidation in a particular period, given that it has survived until the beginning of that period.[9] This graph illustrates the evolution of the overall risk of exit over time. The risk of exit faced by manufacturing firms with 10 or more employees has remained fairly stable over time. It rose in the early 2000s, and then decline to later sharply increased with the

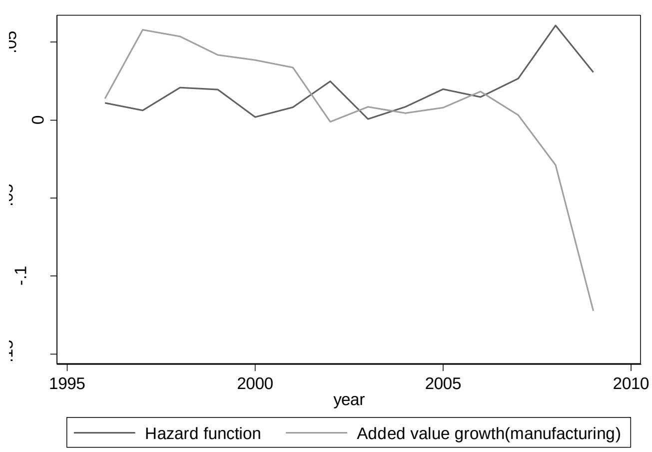
[9] It is estimated as the hazard contribution to the cumulative hazard function between two exit times. This hazard contribution is recorded at all periods t_j at which exit occurs and is obtained as the ratio between the number of exits at time t_j and the number of firms at risk at t_j , before the occurrence of the event.

onset of the current economic crisis. The figure also shows the evolution of the added value in manufacturing. According to the Spanish Statistics Office (INE), the annual average growth rate of added value in the manufacturing was 0.8%, with peaks in the period 1997-2001. By contrast, growth rates decreased steadily since 2007, reaching its lowest value in 2009 (-12.2%).

In order to better understand the effects of the explanatory variables on the exit rate, we start by carrying out non-parametric tests for the equality of hazards functions across groups of firms, according to previously defined explanatory variables. [10] Table 2 presents the results for the log-rank tests. The results indicate the existence of remarkable differences in survival prospects between groups for the vast majority of the explanatory variables considered.

In particular, past-growth rates seem to be relevant in explaining the probability of exiting the market: firms which show heavy shrinks in their size from one year to the other (Low) definitely are associated with higher probabilities of exiting the market, while both fast-growing firms (High) and moderate upsizers and downsizers show much lower probabilities of exiting the market. This fact constitutes a suggestive pattern among different types of firms, and sheds some light on the mechanism of selection by the market. What seems to have the major effect upon the long-run selection mechanism (i.e. the probability of exit) is the heavy shrink, while fast-growing firms and moderate (steady) upsizers and downsizers seem not to have different exiting profiles in the long-run.

Figure 2. Non-parametric hazard function and growth rate



Note: Added value growth is calculated for the whole manufacturing industry by using the National Accounts Statistics.

The innovative effort of the firms seems also to play a key role in explaining the long-run selection mechanism of the market: those firms which undertake R&D investment show much lower exiting probabilities than those which do not undertake these investments, and among those which do spend in research and development, it is interesting to note that those which spend less are the most punished by the market, while a moderate (Medium) profile or a heavy spending profile (High) do not differ much in terms of exiting probabilities.

[10] We have also carried out the Wilcoxon-Breslow-Gehan test and the Peto-Peto-Prentice test, which only differ in the weights used (Cleves et al. 2004), and we have obtained similar results.

With respect to the control variables, some results may be worthy of comment: large firms show lower exiting probabilities than SMEs; older firms are less likely to exit than younger counterparts; family firms are more likely to exit the market with respect to non-family firms and exporting firms are found to exit less than pure domestic firms. No significant differences in survival prospects appear to depend on ownership structure, both for family and foreign capital.

The preliminary evidence presented suggests that exiting the market is associated to some firm characteristics**.** Next, a multivariate regression analysis is carried out in order to assess the effect of each variable on the hazard rate of exiting, once the effect of all the other covariates is controlled for. Table 3 shows the results of estimating the proportional hazards specification under the semi-parametric CPHM distributional assumption for the baseline function. All covariates are introduced as sets of dummy variables with the aim of capturing possible non-linear effects of the covariates on duration. The results largely confirm previous univariate analysis. Three main conclusions can be obtained.

[INSERT TABLE 2 HERE]

Table 2. Non-parametric tests of equality of survival functions by explanatory variables

	Log-rank	Incidence rate
Size	27.96	SMEs 0.0226
	(0.00)	Large 0.0105
H_Growth	67.69	Low 0.0326
	(0.00)	Medium 0.0148
		High 0.0143
Age	6.21	Young 0.0227
	(0.01)	Older 0.0187
Family	0.52	No 0.0186
	(0.47)	Yes 0.0196
Export	40.40	No 0.0270
	(0.00)	Yes 0.0145
Foreign	0.19	No 0.0196
	(0.66)	Yes 0.0168
R&D	44.22	No 0.0239
	(0.00)	Yes 0.0107
H_Tech_effort	45.22	Low 0.239
	(0.00)	Medium 0.0105
		High 0.0107
H_Produc	27.31	Low 0.0276
	(0.00)	Medium 0.0167
		High 0.0154
H_Margin	150.13	Low 0.0388
	(0.00)	Medium 0.0135
		High 0.0105

First, higher growth rates are positively related to survival, though the results suggest non-significant differences between high and medium growth regimes. Second, the results also suggest that firms involved in innovative activities have higher chances of survival. This is very clear for the three set of firm level indicators considered: a binary variable for doing/not doing R&D, a set of dummy variables for technological effort and dummy variables for product and process innovations. In the latter case, the non-significant effect of product innovation is related to high correlation with process innovation. Once each of these variables is taken separately in complementary regressions, a significant effect on survival probability emerges.

Third, we observe a clear effect of age (identified as firms older than 5 years) in firm's survival. In the same way, export activity, family control and better performance exemplified in productivity and operating margin have also a significant influence on survival. By contrast, the econometric analysis suggests that, after controlling for other relevant explanatory factors, the effect of foreign capital participation is negatively associated to survival. Previous papers have also found controversial results with respect to this variable.

Finally, the results for industrial aggregates based on technological effort indicate, by the opposite, that survival probabilities are lower in more technological intensive industries. This is an average industrial result that is compatible with previously obtained on positive effect of firm technological effort. It suggests higher competitive pressures in industries more intensive in knowledge and technological capital, but also that more innovative firms are able to get over this competitive framework by taking advantage of own capabilities.

[INSERT TABLE 3 HERE]

Table 3. Estimation results: Cox estimations

	(1)		(2)		(3)	
	Hazard ratio	P-value	Hazard ratio	P-value	Hazard ratio	P-value
Size	0.701	0.025	0.705	0.029	0.700	0.023
Growth2	0.528	0.000	0.533	0.000	0.535	0.000
Growth3	0.524	0.000	0.524	0.000	0.544	0.000
Age	0.662	0.073	0.673	0.085	0.666	0.075
Family	0.785	0.026	0.794	0.034	0.804	0.044
Foreign	1.473	0.011	1.413	0.023	1.388	0.031
Export	0.687	0.002	0.695	0.002	0.695	0.002
Productivity2	0.872	0.245	0.879	0.272	0.870	0.237
Productivity3	0.862	0.337	0.878	0.401	0.853	0.301
Margin2	0.405	0.000	0.404	0.000	0.416	0.000
Margin3	0.314	0.000	0.314	0.000	0.327	0.000
Innovation:						
Firm-level indicators:						
R&D	0.599	0.000				
Tech_ effort2			0.577	0.002		
Tech_ effort3			0.567	0.002		
Product innovation					0.766	0.111
Process innovation					0.470	0.000
Industry-level indicators:						
Tech_level 2	0.561	0.000				
Tech_level 3	0.803	0.107				
Tech_level 4	1.259	0.324				
KIA			1.560	0.048		
LR chi-squared test (p value)	310.6 (0.000)		267.5 (0.000)		289.8 (0.000)	
Log-likelihood	-2,805.4		-2,816.5		-2,805.6	
N. of observations	21,040		21,124		21,124	
N. of firms	3,320		3,321		3,321	
N. of failures	398		398		398	

Notes:
1. The coefficients indicate the effect on the risk rate of a change from 0 to 1 in the variable.
2. P-values are calculated from robust standard errors.
3. The Cox estimation has been carried out using the method proposed by Efron to deal with ‘‘ties’’ (when there is more than one firm exiting of a particular calendar year).

5. Conclusions

The aim of this paper is to empirically assess the role of firm innovation and growth in explaining the survival of manufacturing firms. To this end, we use non-parametric and semi-parametric survival methods on a representative sample of Spanish manufacturing firms over the period 1995-2010. In contrast to most previous studies that analyze life patterns of a cohort of new firms with a short follow-up period, our database comprises both new and mature firms.

The results indicate, that once we control for a number of firm and industry characteristics, non-innovative and low-growth firms face a remarkable higher risk of failure. These results might provide support for the low effectiveness of the short-run market selection mechanism in punishing and rewarding firms with the reallocation of market shares. Nonetheless, it is relevant to stress that this paper only provides a first step for analyzing the wide range of potential issues related to the dynamics of employment. In particular, only short-term growth is considered. Alternatively, larger time span could be analyzed to observe the influence of medium and long-run firms' growth patterns. Coad et al (2011) provide a recent empirical analysis, where they observe that long lags of growth have a positive effect on firm's chances of survival. However, while they use a cohort of new firms that start to operate at (approximately) the same time, we are dealing with a database with a long time period and a set of very heterogeneous firms with different birth years. Future work is required to implement ways to dig deeper and characterize such medium and long-run growth patterns.

As for innovation, the results show a lower risk of exit for innovative firms. These results hold independently of the specific measure of firm innovation, either input or output. These results are consistent with the predictions of both the selection models and the entry and post-entry literature.

Our findings have some policy implications. Although tentatively, the results provide support to the view that policies promoting the creation of new firms must take into account those factors that may enhance survival, particularly innovation activities by firms. Innovative activities involve sunk costs and uncertainty about their success. Therefore, policies pursued to facilitate these investments (e.g., by reducing costs related to asymmetric information and reducing uncertainty) may have additional social benefits insofar they reduce the likelihood of failure and, consequently, social and economic costs for firms that fail shortly after entry. In that sense, innovation policies turn out to be rather effective strategies for survival. This is even clearer when we consider the increasing tendency towards vertically disintegrated networks of innovation, which emphasize the role of SMEs as key engines of innovation.

Appendix: Industrial and Technological classifications

Industries	NACE rev. 2	Technological intensity (TI)	Knowledge Intensive Activities (KIA)
Meat Products	101	Low	No
Food and tobacco products	102 a 109 + 120	Low	No
Beverages	110	Low	No
Textiles and wearing apparel	131 a 133, 139, 141 a 143	Low	No
Leather and related products	151 + 152	Low	No
Manufacture of wood	161 + 162	Low	No
Paper products	171 + 172	Low	No
Printing and reproduction of recorded media	181 + 182	Low	No
Manufacture of chemicals and pharmaceutical products	201 a 206, 211 + 212	Medium-High* High*	No* Yes*
Manufacture of rubber and plastic products	221 + 222	Medium-Low	No
Manufacture of other non-metallic mineral products	231 a 237, 239	Medium-Low	No
Manufacture of basic metals	241 a 245	Medium-Low	No
Manufacture of fabricated metal products	251 a 257, 259	Medium-Low	No
Manufacture of machinery and equipment	281 a 284, 289	Medium-High	No
Manufacture of computer, electronic and optical products	261 a 268	High	Yes
Manufacture of electrical equipment	271 a 275, 279	Medium-High	No
Manufacture of motor vehicles, trailers and semi-trailers	291 a 293	Medium-High	No
Manufacture of other transport equipment	301 a 304, 309	Medium-High	No
Manufacture of furniture	310	Low	No
Other manufacturing	321 a 325, 329	Low	No

* In the case of pharmaceutical (high-technology), we have used the database information on 3-digits main activity to distinguish between the Manufacture of basic pharmaceutical products and pharmaceutical preparations (High-technology and Knowledge Intensive Activity) and Manufacture of chemicals and chemical products (Medium-high-technology and non Knowledge Intensive Activity).

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