Age and productivity as determinants of firm survival over the product life cycle: an application to Spain

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Abstract

In this paper we make an effort to bridge the gap between the literature on the determinants of firm survival and the theoretical and empirical works on the product life cycle (PLC). Using a representative sample of Spanish manufacturing firms with ten or more employees in the period from 1991 to 2010, we empirically analyze the role played by firm age and productivity on firm survival across the different stages of the PLC. Firm age results to be negatively and significantly correlated with hazard rates mostly in the ‘young’ phase of the PLC (pointing out the role of learning in this phase), while firm productivity is associated with lower hazard rates only in the ‘old’ phase of the PLC when market competition is primarily efficiency-driven. This evidence qualifies the roles of firm age and productivity as determinants of firm survival.

JEL classification: C41, L10, L60

Keywords: Product life cycle; firm survival; discrete time survival methods; Spanish manufacturing firms

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1. Introduction

Despite the extended empirical literature on the determinants of firm survival \(^1\), and the well-developed body of research on the product life cycle (PLC, hereafter), which analyzes industries’ aging patterns in terms of number of firms, innovative activities, entry and exit rates (see the seminal papers by Utterback and Abernathy, 1975; Klepper, 1996), there is relatively scarce empirical evidence enlightening about whether and how firms are qualitatively different at different stages of industry evolution (Peltoniemi, 2011, p. 366).

Actually, the process of evolution under which industries go leads to some transformations in their structures and competitive setting, which may consequently affect the source of competitive advantage and survival of the firms. Thus, the type of surviving firm, that is, the drivers of firm survival, may change with the phase of the life cycle of a product/industry.

Firms’ survival may be considered as the outcome of a (medium-) long-run process of selection among competitors, where either firms show acceptable performance as time passes or they exit the market. That is why, indeed, relevant studies in industrial economics, organizational ecology and strategic management have considered firm survival as a meaningful organizational outcome (see Freeman et al., 1983; Geroski, 1995; Agarwal et al., 2002; Dosi, 2012, among others).

This paper analyzes the determinants of firm survival through the different stages of the product/industry life cycle, with special attention to the role played by firm age and productivity. In particular, the focus lies on examining whether the determinants of firm survival change through the different stages of the PLC. To this end, we use a representative sample of manufacturing firms with ten or more employees taken from the Encuesta Sobre Estrategias Empresariales (ESEE, hereafter), a national survey on business strategies sponsored by the Spanish Ministry of Industry since 1990. The dataset comprises information on 4,546 Spanish manufacturing firms over the period from 1991 to 2010 and includes information on existing firms of all ages. This enables us to estimate the probabilities of exit for a sample of firms characterized by a broad spectrum of ages, and examine whether drivers of firm survival change over different phases of the PLC. This work is an interesting complement to an abundant number of previous studies that have examined the survival of just newly established (born) firms: while those studies have

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\(^1\) As a non-exhaustive list: Mata and Portugal, 1994; Audretsch and Mahmood, 1995 have explored the role of firm initial size; Evans, 1987 has explored the role of firm current size; Freeman et al., 1983; Mata and Portugal, 1994; Mata et al., 1995 have explored the role of firm age; Agarwal, 1997 has explored the role of firm past growth rate; Hannan and Freeman, 1977 have explored the role of narrowness/wideness of the niche a firm occupies in the market; Hall, 1987; Esteve-Pérez and Mañez-Castillejo, 2008 have explored the role of firm R&D spending; Bruderl et al., 1992; Cefis and Marsili, 2005; 2006 have explored the role of firm’s innovative strategies and activities; Doms et al., 1995 has explored the role of firm technological capabilities.
mostly focused on the first years of operation after entry, this paper uses a more comprehensive data set that includes firms of all ages.

The main contribution of this work is twofold. First, it helps to qualify the role of firm age and productivity in explaining firm survival. These two factors have been investigated at length among the most important determinants of firm survival. However, it is legitimate to ask whether or not more experienced or productive firms are always advantaged with respect to their younger and less efficient counterparts or, to some extent, their advantage is specific to the particular phase of the PLC a firm is currently passing through. The empirical analysis is carried out using survival methods that allow accounting for both occurrence and timing of the event of interest (i.e., firm exit).

Second, this paper provides an attempt to deduce the phase of the PLC that a firm is passing through, starting from industry- and firm-level information available in the ESEE survey. Indeed, this approach is quite different from that usually employed in previous studies of the ‘PLC tradition’ which have generally taken the historical evolution of specific products/industries into account, mostly exploiting product- or industry-level information available to researchers (see, among others, Suarez and Utterback, 1995 and Klepper, 2002). Our approach allows including in the analysis firms belonging to different industries, without (necessary) having to have access to seldom available information on specific products or industries for long spans of time.

To anticipate the results, once we control for a large set of firm characteristics, industry unobserved heterogeneity and the economic cycle, we find that firms’ hazard rates in the ‘medium’ and the ‘old’ phases of the PLC are lower than of those in the ‘young’ phase. These results are consistent with the theoretical prediction of PLC models in which a first turbulent phase, characterized by high firm turnover and ‘trial and error’ behavior by entrants, is followed by more ‘stable’ and mature phases. Second, rather interestingly, the role of firm age and productivity changes over the PLC. While firm age is negatively correlated with hazard rates mostly in the ‘young’ phase of the cycle (pointing out the role of learning and experience in this phase), firm productivity is associated with lower hazard rates only in the ‘old’ phase of the cycle when market competition is efficiency driven (Klepper, 1996).

The rest of the paper is structured as follows: Section 2 introduces the framework of analysis. Section 3 describes the data used in the analysis and provides some descriptive statistics. Section 4 presents the econometric methodology and Section 5 discusses the results. Section 6 concludes.
2. Framework of analysis

This paper aims at strengthening the link between two different strands of the literature on firm dynamics in order to investigate whether the role of firm age and productivity changes over the PLC.

On one hand, a large number of papers have studied the determinants of firms exit, immediately after entry (see, for instance, the IJIO’s Special issue on “The Post-Entry Performance of Firms” edited in 1995). To this end, these studies have used information on the early days of a single cohort (or very few cohorts) of entrants followed over a short time span. On the other hand, scholars in the PLC tradition (for instance, Klepper and his co-authors) have investigated the product life cycle of particular products and industries, since its inception to maturity.

In an attempt to bridging the gap between these two strands of the literature, in this paper we use firm-level information to allocate firms to different stages of their product/industry life cycle. The data source used for the analysis is based on the ESEE survey, regularly conducted over a representative sample of existing Spanish manufacturing firms, that includes both broad information at firm-level and some information at the industry-level.

2.1. Deducing the PLC phases of the firms

One of the central issues in the empirical studies within the PLC field of research is the identification of the phases of the PLC. Some years ago Steven Klepper clarified that, in a basic PLC setting,

“[…] three stages of evolution [of a product/industry] are distinguished. In the initial, exploratory or embryonic stage, market volume is low, uncertainty is high, the product design is primitive, and unspecialized machinery is used to manufacture the product. Many firms enter and competition based on product innovation is intense. In the second, intermediate or growth stage, output growth is high, the design of the product begins to stabilize, product innovation declines, and the production process becomes more refined as specialized machinery is substituted for labor. Entry slows and a shakeout of producers occurs. Stage three, the mature stage, corresponds to a mature market. Output growth slows, entry declines further, market shares stabilize, innovations are less significant, and management, marketing, and manufacturing techniques become more refined” (Klepper, 1997, p. 148).
Actually, the majority of previous studies have taken a particular product/industry into account, studying its history from ‘birth’ to the mature stage\(^2\), emphasizing its regularities in terms of number of firms, innovative activities and dynamics of entry/exit and pointing out the technological breakthroughs which have characterized it along its historical evolution, thus being able to identify the single phases of the life cycle for that specific product/industry.

However:

(i) detailed information on the historical evolution of a product/industry in terms of number of firms and product varieties, entry/exit dynamics and technological breakthroughs are not often available to applied researchers;

(ii) the possibility of analyzing more products/industries at the same time may be limited, due to the huge amount of information required; at the same time, multi-product and multi-industry studies would be desirable in order to reach generalizable results.

Accordingly, in this paper we propose a method to deduce the phase of the PLC a firm is passing through based on firm-level information. In particular, four characteristics should serve as dimensions along which to identify three stages of the life cycle of a product/industry.

1. **Predominance of product or process innovation.** Product innovation should outweigh process innovation – both in terms of numbers of firms and intensity within each firm-- in early phases of the life cycle of a given product/industry, where (as suggested by Klepper, 1996) a high number of heterogeneous firms enter the market with new products acting in an ‘entrepreneurial’ regime (Audretsch, 1991) and competing for market dominance (Gort and Klepper, 1982). Conversely, as time passes and the product/industry gets more mature (later phases), market price decreases and only efficient firms investing in process innovation may survive and expand their market share (Klepper, 2002).

2. **The extent of market fragmentation.** In early phases of the PLC the number of firms should rise over time: a high number of firms may act following ‘trial and error’ strategies. However, as time passes and market price decreases, the advantage of being an incumbent (in terms of economies of scale and learning-by-doing) could become insurmountable and entry may virtually stop (Gort and Klepper, 1982; Klepper, 1996). The most efficient firms may even prevent (less efficient) potential

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\(^2\) See, among others, Suarez and Utterback, 1995 who have analyzed the evolution of automobiles, typewriters, transistors, electronic calculators, televisions, and picture tubes industries, and Klepper, 2002 who has analyzed automobiles, tires, televisions and penicillin industries.
competitors from entering the market. Consequently, the number of firms declines making the market more concentrated in the late phases of the life cycle.

3. **The number of product varieties.** In a setting without a technological dominant design\(^3\) (Suarez and Utterback, 1995), a turbulent competition takes place as a process of experimentation of a large variant of products, each one produced at a low scale (sales remain relatively low during this phase, as suggested by Anderson and Tushman, 1990). The emergence of a ‘dominant design’, which marks the shift to the mature stage of product/industry, implies that certain common features are incorporated into the design. As a consequence, in the late phases of the PLC a lower number of product varieties will be sold in the market\(^4\).

4. **The degree of vertical integration.** In early phases of a PLC, the market (demand) will be smaller (lower), and there will be less room for division of labor and specialization (Stigler, 1951). An organized market for intermediate inputs and services would not be developed yet (without the possibility of exploiting economies of scale in the production and provision of inputs), and the ‘typical’ firm would rather lean on internal production in order to fulfill its demand of intermediates and co-ordinate its production process. Thus, in early phases of the PLC, the ‘typical’ firm should show, *ceteris paribus*, a higher degree of vertical integration than in later phases (Klepper, 1997, p. 152).

These four dimensions establish our framework to identify three main phases of the PLC: after having operationalized the four dimensions in an intuitive way, we build a summary indicator based on the co-occurrence of these four dimensions whose proxies are based on industry- and *firm-level information* contained in the ESEE survey.

Roughly (we cross-refer the reader to Section 3.1 for further details on the data and variables employed and how proxies for the four dimensions have been built), for each firm ‘i’, after having standardized between 0 and 1 the proxies for (i) the main ‘type’ (either product or process) of innovation introduced by the firm, \(TINNOV_i\), (ii) the degree of fragmentation of the principal market in which the firm is active, \(FRAG_i\), (iii) the frequency of introduction of new products by the firm and its competitors, \(PVAR_i\), and (iv) a measure of vertical integration of the firm, \(VINT_i\), we calculate the arithmetic average of them:

\[
PLC_i = (0.25) \cdot TINNOV_i + (0.25) \cdot FRAG_i + (0.25) \cdot PVAR_i + (0.25) \cdot VINT_i. \tag{1}
\]

The \(PLC_i\) indicator (and also each of its components’ proxies) ranges from 0 to 1, it is firm-specific and built as time-invariant (see Section 3.1.1 for further explanations).

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\(^3\)In the words of Suarez and Utterback, 1995, p. 416: “A dominant design is a specific path, along an industry’s design hierarchy, which establishes dominance among competing design paths”.

\(^4\)In the theory of Klepper (1996), in later phases of the PLC, product diversity decreases.
Values of the indicator close to 1 (0) characterize the ‘typical’ firm operating in a young (old) phase of its PLC: a firm in a young (old) phase of its PLC should introduce more (less) product than process innovation and should be active in a more (less) fragmented market in which a bigger (smaller) number of product varieties are sold; it should be also characterized by a more (less) vertically integrated structure.

After having built the indicator, we assign firms belonging to different percentile of the $PLC_i$ distribution to different phases (one firm to only one phase). Finally, once the phase has been identified, we investigate whether the effects of firm age and productivity on firm survival are different along the different stages of the PLC.

2.2. Do the effects of firm age and productivity on survival change across different phases of the PLC?

The literature on PLC is rich and has identified the characteristics of an industry in different phases of its life cycle. Nonetheless, little is known about how firm characteristics traditionally thought as determinants of firm survival evolve (gaining or losing significance) as time passes and the product/industry moves from the ‘young’ to the ‘old’ phase. We are mainly thinking about (i) the role of ‘learning’ -- proxied by firm age -- and (ii) the role of firm productivity.

Firm age is a proxy for ‘learning’ processes which take place as time passes. In the ‘passive’ learning model by Jovanovic (1982), firms become more conscious about their uncertain ‘type’ (level of efficiency) as time passes and adjust their growth rates with the updated expectation about their ‘type’. In ‘active’ learning models (Erickson and Pakes, 1995), firm ‘type’ can be partially modified through purposive investments in the development of new technologies. Summing up, in both families of models, firm age definitely helps in dispelling the uncertainty about the firm ‘type’ but does not provide any advantage to survive per se. Conversely, if a ‘learning-by-doing’ process á la Arrow (1962) is at work, young firms may be truly disadvantaged with respect to their older counterparts in terms of (efficiency and thus) survival because of less time accumulated for practice and self-perfection strategies.

However, the advantage of older and more experienced firms over their younger counterparts may be not independent of the phase of the life cycle of their product/industry.

Indeed, the positive effect of age in explaining firm survival may be reduced in later phases for different reasons. On the one hand, this may happen because of the reduced relevance of experimenting with trial and error (see Klepper, 1997, p. 148; Agarwal and Gort, 2002, p. 187) and, consequently, the reduced role of learning-by-doing. On the other hand, this may due also to the lower amount of young firms entering the market as the
product/industry gets more mature: following the framework proposed by Klepper (2002), at later stages of the PLC --given tougher competition in terms of the necessary level of efficiency to survive-- only the most efficient young firms may continue to enter the market, thus showing lower rates of failure with respect to coetaneous firms in other phases. We thus expect that:

*Hp1* - Older firms are advantaged (in terms of lower hazard rates) with respect to their younger counterparts, but this relationship is stronger in early phases of the PLC.

Productivity may be especially relevant for survival in the older phases of the PLC. In fact, following Klepper’s approach, it is during mature phases that firms—facing higher price competition—are forced to compete in terms of decreasing their average costs through boosts in R&D spending in new processes and spreading them over a larger scale (Klepper, 1996; 2002).

*Hp2* - More productive firms are advantaged (in terms of lower hazard rates) with respect to less productive ones, but this relationship is stronger in older phases of the PLC.

3. Data and descriptive analysis

3.1. Data: the ESEE survey

The data used in this paper are taken from the ESEE Survey and refer to the period 1991-2010. The ESEE is an annual survey of Spanish manufacturing firms sponsored by the Ministry of Industry and carried out since 1990. The survey excludes firms with less than 10 employees, while firms with 10 to 200 employees are randomly sampled by industry (20 two-digits NACE rev.2 industries) and size strata (4 groups). Firms larger than 200 employees are surveyed exhaustively, resulting in a response rate of approximately 60% of the population. The survey is well suited to pursue firm-level analysis since it provides rich information on firm characteristics and strategic choices (i.e. innovative activities, information on products and competitors, firms’ sub-contracting activities, advertising, internationalization strategies, etc.), which result to be key in our case in order to identify different phases of a PLC. The survey also provides information on the date of entry to the market (date of birth, which is the one we use in this paper) and to the survey (when a firm first comes under observation). Besides, the survey allows identifying whether a firm stays in business, exits the market or leaves the survey.

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5 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](http://funep.es) for further details).

6 Note that the ESEE is not a mandatory survey.
The data set used in the analysis is an unbalanced panel of 4,546 firms (of all ages) over the period 1991-2010. We compute a firm as exiting in period t when this is the last year the firm is in business. Therefore, information in 2010 is only used to identify those firms exiting in 2009.

3.1.1. Identification of the phases of the PLC

As introduced in the Section 2.1., the identification of the phase is based on the co-occurrence of four dimensions and the PLC_i indicator is a summary measure of all of them based on firm-level information.

1. The first dimension is related to the main type of innovation introduced by the firm during the period under analysis. We use dichotomous information on whether a firm has introduced a product and/or process innovation or not in each year t in which is observed. Thus, TINNOV_i is built as the ratio between the number of years a firm has introduced at least 1 product innovation and the number of years a firm has introduced at least 1 process innovation.

\[
TINNOV_i = \begin{cases} 
\frac{\sum_t d_{\text{product innovation}_i t}}{\sum_t d_{\text{process innovation}_i t}} & \text{if } \sum_t d_{\text{process innovation}_i t} \neq 0 \\
\sum_t d_{\text{product innovation}_i t} & \text{if } \sum_t d_{\text{process innovation}_i t} = 0 \land \sum_t d_{\text{product innovation}_i t} \neq 0 \\
0 & \text{if } \sum_t d_{\text{process innovation}_i t} = 0 \land \sum_t d_{\text{product innovation}_i t} = 0 
\end{cases}
\]

where both \( d_{\text{product innovation}_i t} \) and \( d_{\text{process innovation}_i t} \) can be either equal to 0 or 1 in each year t. We standardize the variable between 0 and 1.

2. The second dimension is the degree of market fragmentation (FRAG_i), in terms of the number of competitors that the firm faces. The variable is built as the average --over the period of time during which a firm is observed-- of dichotomous yearly information on the fragmentation of the industry in which the firm conducts its business. In particular:

\[
FRAG_i = \frac{\sum_t d_{\text{fragmkt}_i t}}{t}
\]

where \( d_{\text{fragmkt}_i t} = 1 \) when the number of competitors (with a significant market share) is bigger than 25 in a given year t, and 0 otherwise.

3. The average propensity for the firm and its competitors to introduce new variants of product (PVAR_i) is the third dimension which is taken into account by the PLC_i indicator in order to identify the phase of the PLC.

\[
PVAR_i = \frac{\sum_t d_{\text{prodvar}_i t}}{t}
\]
where \( d_{prodvar} = 1 \) when both the firm and its competitor have introduced new variants of the product in a given year \( t \), and 0 otherwise.

4. Finally, the average degree of vertical integration \((VINT_i)\) of the firm, measured as the reciprocal of the average percentage of intermediate inputs sub-contracted to other firms is the fourth and final dimension which is included in the \( PLC_i \) indicator. We take the average over the entire period of time during which a firm is observed and standardize the variable between 0 and 1 before including it in the empirical analysis.

Overall, each dimension is captured by a time-invariant proxy, i.e. one firm shows the same value of the proxy for that dimension along the years during which it is observed.

After having calculated the value of each dimension for each firm, we can calculate the arithmetic sum of these four dimensions, as specified in Equation 1. By construction the summary indicator for each firm varies between 0 and 1 and it is time-invariant too, i.e. each firm shows the same value of the indicator for all years during which it is observed in the database: this has been done in order to (i) avoid time-inconsistencies and (ii) simplify the identification of the phases whose procedure is detailed below. Values of the indicator close to 1 (0) characterize the firms operating in a young (old) phase of its PLC.

In order to get further insights on the PLC indicator, Table 1 reports some preliminary statistics referring to it. Although the particular value of the indicator is of little interest, its distribution gives an idea of the relative positioning of the bulk of firms in our sample with respect to an indicator that ranges from 0 to 1. Actually, even though some firms show relatively high values of the PLC indicator (the top 5% shows values higher than 0.6) the majority of firms in the sample are concentrated around low values of the indicator. Indeed, at least the 50% of the firms shows values lower than 0.4. This may be related to the fact that the vast majority of Spanish manufacturing firms are currently passing through relatively ‘old’ phases of their PLC. Similar conclusions can be reached from Figure 1, which depicts the distribution of the PLC indicator, taking only 1 observation for each firm (recall that the value of the indicator is time-invariant for each firm).

After having built the indicator, we allocate firms to the three possible stages of their PLC according to their relative position in the distribution of \( PLC_i \) (one firm to only one phase). In particular, we assign the top 25% firms (values of the \( PLC_i \) indicator closer to 1) to the phase of the PLC named ‘young’ and the bottom 25% to the phase named ‘old’ (values of the \( PLC_i \) indicator closer to 0). The remaining 25%-75% of the distribution are assigned to the intermediate phase ‘medium’.
## Table 1 - Values of the PLC indicator

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Values of the PLC indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>0.2041</td>
</tr>
<tr>
<td>5%</td>
<td>0.2790</td>
</tr>
<tr>
<td>10%</td>
<td>0.3058</td>
</tr>
<tr>
<td>25%</td>
<td>0.3272</td>
</tr>
<tr>
<td>50%</td>
<td>0.3897</td>
</tr>
<tr>
<td>75%</td>
<td>0.4833</td>
</tr>
<tr>
<td>90%</td>
<td>0.5772</td>
</tr>
<tr>
<td>95%</td>
<td>0.6292</td>
</tr>
<tr>
<td>99%</td>
<td>0.7479</td>
</tr>
</tbody>
</table>

| Min       | 0.0874                     |
| Max       | 0.9132                     |
| Mean      | 0.4143                     |
| Standard deviation | 0.1125            |
| Firms     | 4,546                      |

## Figure 1 - Values of the PLC indicator

![Histogram of PLC indicator values](image)
3.1.2. Firm age and firm productivity over the PLC

In this section we explain how firm age and firm productivity enter the econometric model. These (as well as controls, Section 3.2.3) are introduced as vectors of dummy variables because of easiness of interpretation and to capture possible non-linearities in their effects on survival chances. Moreover, vectors of dummies have been built starting from time-varying variables thus being able to account for possible changes in their effects over time. Finally, all explanatory variables are lagged one period in order to reduce endogeneity concerns.

- **Firm age** is calculated as the difference between year \( t \) (first year in which the firm is observable) and the year of establishment of the firm. We employ the taxonomy adopted by Barba Navaretti et al. (2014) and firm age enters the econometric model as a \((j-1)\) vector of dummy variables, \( \text{AGE}_j \), where:
  \[
  j = \begin{cases} 
    1 & \text{if } 0 < \text{AGE}_{it} \leq 10 \\
    2 & \text{if } 11 \leq \text{AGE}_{it} \leq 20 \\
    3 & \text{if } 21 \leq \text{AGE}_{it} < \text{max} 
  \end{cases}
  \]

- **Firm productivity** has been calculated as real labor productivity as the ratio between gross value added at constant (1990) prices over total employment in each year \( t \). After having calculated the value of productivity at the 25\(^{th}\) and 75\(^{th}\) percentile of its distribution, we introduce the variable in the econometric model as a vector of \((p-1)\) dummy variables, \( \text{PRODUCTIVITY}_p \), where:
  \[
  p = \begin{cases} 
    1 & \text{if } \text{PRODUCTIVITY}_{it} \leq \text{PRODUCTIVITY}^{25th} \\
    2 & \text{if } \text{PRODUCTIVITY}^{25th} < \text{PRODUCTIVITY}_{it} \leq \text{PRODUCTIVITY}^{75th} \\
    3 & \text{if } \text{PRODUCTIVITY}_{it} > \text{PRODUCTIVITY}^{75th} 
  \end{cases}
  \]

3.1.3. Control variables

In order to minimize the risk of spurious correlations, it is necessary to introduce a vector of controls, as suggested by previous works on the determinants of firm survival. In particular, the vector includes the following variables.

- A measure of **firm size**, defined as the total number of employees at the end of the year. Firm size has been traditionally considered a relevant determinant of firm survival, being an indicator of a measure of (minimum) efficient scale and resources which ensure a period of quite life to the firm (see, among others, Evans, 1987; Mata and Portugal, 1994; Audretsch and Mahmood, 1995; Coad et al. 2013). We define two groups of firms and the corresponding dummy variables: those from 10 to 49 employees, \( \text{SIZE}_{S} \), and those with more than 49 employees, \( \text{SIZE}_{L} \) and introduce only the second dummy in the econometric model to avoid multicollinearity;
• A measure of **firm profitability**, calculated as the EBITDA\(^7\) margin (EBITDA/sales) at the end of the year. It is reasonable to expect that in the medium-long run chances of firm survival are affected by the ability of firms to generate stable flows of earnings to remunerate all factors of production (see, among others, Bellone et al., 2008). After having calculated the value of the EBITDA margin at the 25\(^{th}\) and 75\(^{th}\) percentile of its distribution, we define three dummy variables, respectively indicating low profitable firms (those with a value lower than the 25\(^{th}\) percentile), EBITDAM\(_L\), medium profitable firms (value between the 25\(^{th}\) and the 75\(^{th}\) percentile), EBITDAM\(_M\), and high profitable firms (value higher than the 75\(^{th}\) percentile), EBITDAM\(_H\). We introduce two out of three dummies in the econometric model to avoid multicollinearity.

• A measure of **R&D efforts**, calculated as the ratio between the number of employees in R&D activities and total number of firm employees at the end of the year. Firms are able to increase the likelihood of their survival through R&D efforts which lead to cost reduction, quality improvement, new product development or other innovative activities (see, among others, Kim and Lee, 2011). After having calculated the median value of the ratio for the entire sample, we define three groups of firms and their corresponding dummy variables: those firms with zero R&D employees, R&D\(_L\), those with showing ratio below the median value, R&D\(_M\), and those showing a ratio above the median value, R&D\(_H\). We introduce two out of three dummies in the econometric model to avoid multicollinearity.

• A dummy variable taking value equal to 1 for **multi-plant firms**, MULTIPLANT, and taking value 0 otherwise. In difficult situations, multi-plant firms can bear the failure of one of their plants without failing themselves, while single-plant cannot (Mata and Portugal, 1994).

• A dummy variable taking value equal to 1 for those firms with part of their equity capital owned by **foreign investors**, FOREIGN, and taking value 0 otherwise. Foreign participation may foster access to foreign technology, which could improve the firm efficiency and survival chances. Yet, the empirical evidence is not conclusive (Görg and Strobl, 2003; and Mata and Portugal, 2002, 2004).

• A dummy variable taking value equal to 1 for those firms in which there is **no separation between ownership and control** as a proxy for **family firms**, FAMILY, and taking value 0 otherwise. Family goal may be that of preserving the firm to future family generations, thus family members will take actions to increase the probability of firm survival with respect to non-family firms (see, Colli, 2012, among others).

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\(^7\) EBITDA stands for “earnings before interest, taxes, depreciation and amortization”.

• A dummy variable, *DIVERSIFICATION*, taking value equal to 1 if the firm shows some extent of product diversification and 0 otherwise. The diversification measure has been calculated using the entropy index originally proposed by Jacquemin and Berry (1979) on sales’ shares across 2-digit industries.

• We finally include a vector of *(I-1)* industry dummies, *SEC*, in the econometric model in order to control for time-invariant industry specific unobserved heterogeneity and a vector of time dummies.

Table 2, which compares firms’ characteristics across the three phases of the PLC, reveals that firms belonging to the three phases are clearly different in several dimensions. On average, firms belonging to the ‘young’ phase of the PLC are younger, smaller, less productive and profitable than their counterparts passing through the ‘medium’ and ‘old’ phases. At the same time they employ a higher share of employees in R&D activities than those firms passing through older phases of the PLC. Moreover, a lower share of firms which have been assigned to the ‘old’ phase of the PLC are family firms with respect to their counterparts assigned to younger phases of the PLC. Finally firms passing through the ‘old’ phase of the PLC are more frequently multi-plant, (at least) partially owned by foreign investors and show more diversified product-portfolios.

Given that firms passing through ‘young’, ‘medium’ and ‘old’ phases of the PLC are different in several dimensions, in order to assess the roles played by firm age and productivity in shaping firm survival prospects across the three phases, it is necessary to conduct a multivariate econometric analysis and examine their effects when the moderating effect of other firm characteristics is taken into account. This will be the focus of the next section.
### Table 2 – Descriptive statistics by phases of the PLC

<table>
<thead>
<tr>
<th>Firm-level characteristics</th>
<th>Measure</th>
<th>Young</th>
<th>Medium</th>
<th>Old</th>
<th>All phases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age = # of years since firm establishment</td>
<td>Median value</td>
<td>19</td>
<td>21</td>
<td>25</td>
<td>22</td>
</tr>
<tr>
<td>Real labor productivity = GVA at constant (1990) prices / total employees</td>
<td>Average value</td>
<td>38200,73</td>
<td>54833,36</td>
<td>59548,38</td>
<td>52372,36</td>
</tr>
<tr>
<td>EBITDA margin = EBITDA / sales</td>
<td>Average value</td>
<td>-0.044</td>
<td>-0.000</td>
<td>0.002</td>
<td>-0.009</td>
</tr>
<tr>
<td>R&amp;D effort = R&amp;D employees / total employees</td>
<td>Percentage</td>
<td>2,12%</td>
<td>1,66%</td>
<td>1,84%</td>
<td>1,80%</td>
</tr>
<tr>
<td>Size = total employees</td>
<td>Median value</td>
<td>36</td>
<td>45</td>
<td>107</td>
<td>49</td>
</tr>
<tr>
<td>Multi-plant firm (= 1 if firm owns &gt; 1 plant)</td>
<td>Share of firms</td>
<td>10,60%</td>
<td>14,70%</td>
<td>20,70%</td>
<td>15,10%</td>
</tr>
<tr>
<td>Foreign capital (=1 if part of firm equity is owned by a foreign investor)</td>
<td>Share of firms</td>
<td>15,00%</td>
<td>19,80%</td>
<td>27,80%</td>
<td>20,60%</td>
</tr>
<tr>
<td>Diversification (=1 if the entropy indicator by Jacquemin and Berry (1979) &gt; 0)</td>
<td>Share of firms</td>
<td>8,10%</td>
<td>8,70%</td>
<td>10,90%</td>
<td>9,00%</td>
</tr>
<tr>
<td>Family firm (=1 if there is NO separation between ownership and control)</td>
<td>Share of firms</td>
<td>49,80%</td>
<td>43,00%</td>
<td>33,70%</td>
<td>42,40%</td>
</tr>
</tbody>
</table>
4. The empirical model

To evaluate the differential effect of firm age and productivity on the likelihood of survival, we use survival methods. A central concept is the hazard rate, that is, the probability of occurrence of an event (i.e. firm exit) conditional on survival up to that period. These methods depict some desirable features. First, they allow controlling for both the occurrence and timing of firm exit. Second, they also appropriately deal with right-censoring, that is, in cases when we only know that a firm has survived up to a given period $t$. Third, these methods easily handle time-varying covariates, which is interesting since survival is related to the ability of a firm to adapt to a changing (and challenging) competitive environment. Fourth, they are also suitable to control for the presence of unobserved firm heterogeneity.

Although the transition event of interest may occur at any particular instant in time (the stochastic process occur in continuous time), the nature of the dataset leads to group survival times into discrete intervals of time (interval-censored data) of one year. That is, the discrete time hazard function or probability of ending the spell in $j$ periods conditional on survival up to $j-1$ periods.

$$h_j(j) = \Pr(j - 1 < T_j \leq j \mid T_j > j - 1) = \frac{\Pr(j - 1 < T_j \leq j)}{\Pr(T_j > j - 1)}$$ (2)

In order to assess the effect of explanatory variable, we estimate a complementary log-log model ($\text{cloglog}$), a discrete time version of the piece-wise exponential proportional hazard model\(^8\). Hence, assuming that the discrete hazard rate follows a complementary log-log distribution (Prentice and Gloeckler, 1978) and allowing for unobserved individual heterogeneity, the hazard rate takes the form:

$$\text{cloglog} \left[ 1 - h_j(X \mid \nu) \right] = \log \left( -\log \left[ 1 - h_j(X \mid \nu) \right] \right) = \beta' X + \gamma_j + u$$ (3)

where $\gamma_j$ is the interval baseline hazard and summarizes the pattern of duration dependence, which we parameterize as piece-wise constant including four time dummies for four sub-periods (1991-95; 1996-2000; 2001-2005; 2006-2009).

We are interested in identifying the $\beta$ parameters, which show the effect of the explanatory variables included in vector $X$ on the hazard rate. The baseline hazard (when covariates equal to 0) varies over duration-time intervals, but the effect of covariates is constrained to be a constant (over duration time) proportional shift of the baseline hazard function common to all spells.

\(^8\) See Jenkins (2005) for an excellent overview of complementary log-log and proportional hazards models.
We also incorporate firm-level random effects by means of an error term $u = \log(\nu)$ that is assumed to be normally distributed with zero mean and variance $\sigma^2$. This is the so-called frailty term and allows controlling for unobserved individual heterogeneity. In the empirical analysis we test whether the variance of the frailty term is statistically different from zero, which would suggest that the unobserved heterogeneity is important. If this variance is not statistically different from zero, then a non-frailty model would be the preferred specification. To obtain efficient estimators and unbiased standard errors, we apply the Huber-White sandwich or robust estimator.

A desirable feature of this estimation model, which makes it suitable for our analysis, is that it is only the ordering of exit times that matters for the estimation, rather than the actual times by themselves. This is an important feature given that our analysis is based on calendar time. Hence, as calendar time changes, the risk of suffering the event of failure also changes. Hence, the baseline hazard function controls for the overall evolution of risk common to all firms in the market during a particular time-interval, independently of the age of the firm (for instance, risk of exit related to macroeconomic business cycle). Therefore, firm age is included in the model as an explanatory variable.

5. Econometric results

In this section we present the results related to the estimation of reduced form discrete time survival models. First, in order to control for the presence of unobserved firm-level heterogeneity (related to unobserved firm organizational capabilities, access to specific assets, etc., which may affect firm survival chances), we have estimated frailty survival models: the null hypothesis of no unobserved individual heterogeneity cannot be rejected at a 1% of significance level. Hence, the non-frailty models are the appropriate models to estimate. Second, to obtain efficient estimates and unbiased standard errors, we employ robust estimators.

It is relevant to clarify that tables of results report hazard ratios. A unit change in a variable leads to a proportional shift in the conditional probability of exit. A hazard ratio smaller (greater) than one means a negative (positive) effect of the explanatory variable on the hazard rate. That is, when the hazard ratio is smaller (greater) than one, the effect of the corresponding covariate is to decrease (increase) the hazard rate.

Table 3 shows the result of the regressions, inserting the phases of the PLC as regressors and pooling the observations referring to the three phases together. We

---

9 The lack of control for unobserved heterogeneity may lead to the over-estimation the degree of negative duration dependence in the hazard as a result of a selection process that, as time goes by, leaves alive a higher proportion of “well-suited to survive” firms. A second effect of neglecting individual unobserved heterogeneity is the under-estimation of the true proportional response of the hazard to a change in an explanatory variable.
include two out of three corresponding dummies, taking the ‘young’ phase as our ‘baseline’. In this case, *PHASE_MEDIUM* and *PHASE_OLD* should capture the heterogeneity—in terms of hazard rates—across the phases contemporaneously assuming firms’ characteristics (i.e. age, productivity and controls) to have the same effect across the three phases. We will later relax this assumption, checking if firm age and firm productivity have different effect on hazard rates across the three phases of the PLC.

**Table 3 - Econometric results: pooling the observations of the three phases**

<table>
<thead>
<tr>
<th>Dependent variable: hazard rates</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHASE_MEDIUM</td>
<td>0.663</td>
<td>0.676</td>
<td>0.722</td>
<td>0.811</td>
<td>**</td>
</tr>
<tr>
<td>PHASE_OLD</td>
<td>0.768</td>
<td>**</td>
<td>0.802</td>
<td>**</td>
<td>0.939</td>
</tr>
<tr>
<td>AGE_2</td>
<td>0.727</td>
<td>***</td>
<td>0.747</td>
<td>***</td>
<td>0.787</td>
</tr>
<tr>
<td>AGE_3</td>
<td>0.592</td>
<td>***</td>
<td>0.679</td>
<td>***</td>
<td>0.805</td>
</tr>
<tr>
<td>PRODUCTIVITY_M</td>
<td>0.497</td>
<td>***</td>
<td>0.824</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>PRODUCTIVITY_H</td>
<td>0.376</td>
<td>***</td>
<td>0.757</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>EBITDAM_M</td>
<td>0.298</td>
<td>***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EBITDAM_H</td>
<td></td>
<td>0.331</td>
<td>***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D_M</td>
<td></td>
<td>0.436</td>
<td>***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D_H</td>
<td></td>
<td>0.711</td>
<td>***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIZE_L</td>
<td></td>
<td>0.680</td>
<td>***</td>
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<tr>
<td>MULTIPLANT</td>
<td></td>
<td>0.646</td>
<td>***</td>
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<tr>
<td>FOREIGN</td>
<td></td>
<td>1.174</td>
<td></td>
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</tr>
<tr>
<td>DIVERSIFICATION</td>
<td></td>
<td></td>
<td></td>
<td>1.062</td>
<td></td>
</tr>
<tr>
<td>FAMILY</td>
<td></td>
<td></td>
<td></td>
<td>0.803</td>
<td>**</td>
</tr>
<tr>
<td>Textiles, wearing apparel,</td>
<td></td>
<td></td>
<td></td>
<td>3.563</td>
<td>***</td>
</tr>
<tr>
<td>leather and footwear</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wood, paper and printing</td>
<td></td>
<td></td>
<td></td>
<td>2.419</td>
<td>***</td>
</tr>
<tr>
<td>Chemicals, pharmaceutical</td>
<td></td>
<td></td>
<td></td>
<td>1.383</td>
<td></td>
</tr>
<tr>
<td>products, rubber and plastics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mineral products and metals</td>
<td></td>
<td></td>
<td></td>
<td>1.511</td>
<td>**</td>
</tr>
<tr>
<td>Machinery, computers, electrical</td>
<td></td>
<td></td>
<td></td>
<td>1.706</td>
<td>***</td>
</tr>
<tr>
<td>and electronic equipment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motor vehicles and other</td>
<td></td>
<td></td>
<td></td>
<td>1.209</td>
<td></td>
</tr>
<tr>
<td>transport equipment</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Furnitures and other</td>
<td></td>
<td></td>
<td></td>
<td>2.116</td>
<td>***</td>
</tr>
<tr>
<td>manufacturing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1991-1995</td>
<td>0.0239</td>
<td>***</td>
<td>0.0316</td>
<td>***</td>
<td>0.0414</td>
</tr>
<tr>
<td>1996-2000</td>
<td>0.0133</td>
<td>***</td>
<td>0.0176</td>
<td>***</td>
<td>0.0236</td>
</tr>
<tr>
<td>2001-2005</td>
<td>0.0141</td>
<td>***</td>
<td>0.0188</td>
<td>***</td>
<td>0.0262</td>
</tr>
<tr>
<td>2006-2009</td>
<td>0.0335</td>
<td>***</td>
<td>0.0438</td>
<td>***</td>
<td>0.0642</td>
</tr>
<tr>
<td>Observations</td>
<td>34,639</td>
<td>34,639</td>
<td>34,639</td>
<td>34,591</td>
<td>33,817</td>
</tr>
</tbody>
</table>

*Note: SEC1 (excluded sector): Food, beverages and tobacco.*

Column 1 of Table 2 shows the result of the regression including only the set of time dummies referring to the four sub-periods under analysis. Results are not very informative *per se* and simply control for different risks of exit (hazards) across the four different sub-periods, capturing the role of the business cycle.

Column 2 is more interesting, showing the different hazard rates characterizing firms belonging to each phase of the PLC: in particular, firms which are passing through the
‘medium’ and ‘old’ phases show lower hazard rates than firms which are passing through the ‘young’ phase. This result is in line with PLC models which predict a first turbulent phase characterized by a high turnover of firms that conduct a strategy of ‘trial and error’; after this phase, the market starts becoming more stable.

Column 3 shows the effect of firm age on firm survival, conditional to the phase of the PLC. Age, as expected (Freeman et al., 1983; Mata and Portugal, 1994; Mata et al., 1995), shows a clear negative relationship with hazard rates, with older firms (those which are active since more than 20 years) showing a hazard rate which is about 40% lower than the youngest (baseline and omitted) group.

When we introduce the measure of productivity in the empirical model (column 4), we get some interesting results. First, more productive firms (especially those in the highest group of productivity, PRODUCTIVITY_H) show a sizeable and significant lower risk than their least productive counterparts (Jovanovic, 1982; Ericson and Pakes, 1995). Second, part of the explanatory power previously (column 3) attributed to age is now captured by productivity, suggesting that older firms (which have been active in the market for a long period of time) are those which have performed better in terms of efficiency levels. Third, the oldest phase of the cycle (PHASE_OLD) loses its explanatory power. This last result is very interesting and, in some sense, is in line with PLC models. These models predict that in the ‘old’ phases of the cycle market competition will be efficiency-driven, with firms forced to compete in terms of decreasing their average costs through boosts in R&D spending in new processes and spreading them over a larger scale (Klepper, 1996). Thus, productivity may capture and ‘explain’ differences in hazard rates between the ‘young’ (baseline and omitted phase) and the ‘old’ phase (PHASE_OLD).

Finally, when we include the full set of controls in the econometric analysis, the non-significant difference in terms of hazard rates between the ‘young’ and ‘old’ phase is confirmed, while the ‘medium’ phase still shows a lower hazard rate than the other two phases, confirming itself as a relatively ‘stable’ phase of the life cycle. Ceteris paribus, the older and more productive firms show lower hazard rates.

The value of coefficients referring to some controls is also worthy of comment. More profitable firms (EBITDA_M and EBITDA_H) show lower hazard rates than those which have performed the worst in terms of profitability (EBITDA_L), confirming previous works in the field (Bellone et al., 2008). Firms which have employed larger shares of their workforce in R&D activities show lower hazard rates than their counterparts (Kim and Lee, 2011). Larger firms, as expected, show lower hazard rates than their smaller counterparts; the same is true for multiplant firms and family-owned firms. Somehow surprisingly, neither (partially) foreign-owned firms nor diversified firms show hazard rates statistically different from the reference category.
We are interested in understanding if firm age and firm productivity play a consistent (or, conversely, changing) role across the three phases of the PLC. In order to do that we estimate separate regressions for each phase and report the results in Table 4.

We find indeed that firm age and productivity play different ‘roles’ across different phases of the life cycle. When we include firm age alone in the regressions (column 1), the oldest firms (AGE_3) show lower hazard rates than younger counterparts, but this seems especially true in the ‘young’ phase of the product cycle. This result may arise as a result of (i) the higher amount of young firms entering the market in the early days, (ii) the higher amount of ‘trial and error’ and (iii) the higher relevance of learning-by-doing (Klepper, 1997; Agarwal and Gort, 2002).

When productivity is introduced in the empirical model (column 2), age loses part of its explanatory power for explaining firms’ survival prospects. This is even more evident in the ‘old’ phase of the cycle where, age is barely significant only for explaining the lower hazard rates of very old firms (AGE_3). Moreover, the most productive firms result to be characterized by lower hazard rates (even 65% lower) than the least productive ones during the ‘old’ phases of the PLC pointing out that being efficient is relevant for firm survival especially in the ‘old’ phase of the PLC when market competition is essentially efficiency-driven.

When we introduce the full vector of controls in the regressions (column 3), results of columns 1 and 2 are confirmed and, to some extent, they are even strengthened. The roles of firm age and firm productivity are totally ‘polarized’ in the two extreme phases of the PLC. On the one hand, in the ‘young’ phase, firm age explains the differences in hazard rates between young and old firms, possibly capturing the learning phenomenon which should be relevant in that phase. Conversely, there arise no significant effects of firm age on survival prospects in medium and old stages of the life cycle. On the other hand, during the ‘old’ phase it is key to ‘be efficient’ in order to stay in the market (survive) and persistently show an advantage over competitors.

As for control variables, more profitable firms maintain their advantage in terms of lower hazard rates with respect to their less profitable counterparts during all three phases. Firms characterized by stronger R&D efforts maintain their advantage with respect to their more R&D-‘lazy’ counterparts especially in the ‘old’ phase of the cycle. Larger firms show lower hazard rates than their smaller counterparts but this is especially true in the ‘medium’ phase. The other controls (MULTIPLANT, FOREIGN, FAMILY, DIVERSIFICATION) maintain the signs found in the ‘pool’ estimation (Table 2) but they are statistically significant only in some specific phases. Interestingly enough, industry dummies are statistically significant in explaining difference in hazard rates between sectors only in ‘medium’ and ‘old’ phases of the PLC: this may be due to the fact that, when a new product is introduced and a new industry created, it takes some time for that
product/industry to develop a specific competitive setting. This may be a clue that industry-specific characteristics that shape competitive environment and industry dynamics are relatively less important in the early days of the industries, where not even a “dominant design” has emerged. In contrast, in later stages, the particular industry firms are in may shape the required characteristics that make firms fit enough to survive.
Table 4 – Econometric results: separate regressions for the three phases

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Phase ‘young’</td>
<td>Phase ‘medium’</td>
<td>Phase ‘old’</td>
</tr>
<tr>
<td><strong>AGE_2</strong></td>
<td>0.540    ***</td>
<td>0.709</td>
<td>0.743</td>
</tr>
</tbody>
</table>
| **AGE_3**            | 0.589    ***     | 0.617    **       | 0.773             | 0.665    **     | 0.702             | 0.695             | *
| **PRODUCTIVITY_M**   | 0.561    ***     | 0.519             | 0.381             | 0.829    ***     | 0.966             | 0.572             | ***
| **PRODUCTIVITY_H**   | 0.366    ***     | 0.370             | 0.357             | 0.595    ***     | 0.921             | 0.629             | *      |
| **EBITDAM_M**        | 0.332    ***     | 0.252             | 0.357             | 0.385    ***     | 0.259             | 0.483             | ***
| **EBITDAM_H**        | 0.385    ***     | 0.259             | 0.483             | 0.372    ***     | 0.409             | 0.532             | **    |
| **R&D_M**            | 0.981    **      | 0.565             | 0.674             | 0.973    **      | 0.731             | 0.566             | *      |
| **R&D_H**            | 0.973    **      | 0.565             | 0.674             | 0.627    **      | 0.731             | 0.566             | *      |
| **SIZE_L**           | 1.498    ***     | 0.896             | 1.394             | 1.619    ***     | 1.069             | 0.606             |
| **MULTIPLANT**       | 0.950    **      | 0.753             | 0.721             | 0.950    **      | 0.753             | 0.721             |
| **FOREIGN**          | 2.439    **      | 4.257             | 4.120             | 1.793    **      | 2.251             | 3.261             | ***    |
| **DIVERSIFICATION**  | 1.929    **      | 1.318             | 1.989             | 1.422    **      | 1.480             | 1.620             |
|                              | 1.099    **      | 2.075             | 1.711             | 1.072    **      | 1.083             | 1.476             |
|                              | 1.638    **      | 2.059             | 2.870             | 1.638    **      | 2.059             | 2.870             | **    |
| **1991-1995**        | 0.0498    ***    | 0.0239            | 0.0351            | 0.0470    ***    | 0.0346            | 0.065             | ***    |
|                      | 0.0313    ***    | 0.0138            | 0.0168            | 0.0434    ***    | 0.0213            | 0.033             | ***    |
|                      | 0.0293    ***    | 0.0167            | 0.0201            | 0.0398    ***    | 0.0253            | 0.040             | ***    |
|                      | 0.0554    ***    | 0.0465            | 0.0502            | 0.0766    ***    | 0.0692            | 0.0975            | ***    |
| **Observations**      | 7,266     | 19,814            | 7,559             | 7,259     | 19,780            | 7,552             | 7,186     | 19,273             | 7,358             |

Note: SEC1 (excluded sector): Food, beverages and tobacco.
6. Concluding remarks

Despite the extended empirical literature on the determinants of firm survival, little is known about how characteristics of surviving firms evolve across different phases of the PLC (Peltoniemi, 2011, p. 366). This is unfortunate because the process of evolution under which industries go leads to some transformations in their structures and competitive setting, which may consequently affect the source of competitive advantage and survival of the firms.

This paper -- in an attempt to bridge the gaps between these two strands of the literature on industrial dynamics -- empirically analyzes the role played by firm age and productivity on firm survival across different phases of the PLC, making use of a representative sample of Spanish manufacturing firms with ten or more employees in the period from 1991 to 2010.

Once we control for a large set of firm characteristics, industry unobserved heterogeneity and the economic cycle, we find that (as predicted by PLC models) firms’ hazard rates in the ‘medium’ and the ‘old’ phase of the product/industry life cycle are lower than of those in the ‘young’ phase. Moreover, the roles of firm age and productivity do change across the stages of the PLC. While firm age is negatively and significantly correlated with hazard rates mostly in the ‘young’ phase of the PLC (pointing out the role of learning and experience in that phase), firm productivity is associated with lower hazard rates only in the ‘old’ phase of the cycle when market competition is mainly efficiency-driven (Klepper, 1996).

The main contribution of this work is twofold. First, it helps to qualify the role of firm age and productivity in explaining firm survival: these two factors have been investigated at length among the most important determinants of firm survival but it is legitimate to ask whether or not more experienced and/or productive firms are always advantaged with respect to their younger and less efficient counterparts or, to some extent, their advantage is ‘phase’-specific. Second, this paper provides an attempt to deduce the phase of the PLC that a firm is passing through, starting from industry- and firm-level information available in the ESEE survey. This makes this work an interesting complement to the vast body of works within the PLC tradition which have usually taken the historical evolution of specific products/industries into account by exploiting product- or industry-level information available to researchers (see, among others, Suarez and Utterback, 1995 and Klepper, 2002).

Finally, results may help to lay out some implications both for management and policy makers. On the one hand, during the young phase of a PLC it may be particularly relevant for firms to push for experimentation of new products by means of trial and error strategies. Here younger managers with a more risk-loving attitude (Cucculelli and Ermini,
2012; Barba Navaretti et al., 2014) may be more effective in introducing innovations and surviving market competition. During this phase the elimination of barriers to entrepreneurship and the existence of proper mechanisms of access to credit (particularly needed by young firms) not biased against new businesses may be particularly helpful. On the other hand, during more mature phases of a PLC it would be key for firms to reach high levels of efficiency: this may be reached, for example, by pursuing larger scales of operation or by fostering firm restructuring through sub-contracting strategies. Both strategies may be incentivized by ad hoc industrial policies.

References


