Age and productivity as determinants of firm survival over the industry life cycle

Silviano Esteve-Pérez[a]

Fabio Pieri[b]

Diego Rodriguez[c]

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Abstract

This paper contributes to fill the gap between the literature on the determinants of firm survival and the empirical works on the industry life cycle (ILC). Using a representative sample of Spanish firms with ten or more employees over the period 1993-2009, the role played by firm age and productivity in firm survival is empirically analyzed across three stages of the life cycle of forty-seven 3-digit manufacturing sectors. In the "early" stage of the ILC, firm age is negatively correlated with hazard rates while firm productivity is not. Firm productivity is associated with lower hazard in the "mature" stage of the ILC, when competition is primarily efficiency-driven, while firm age does not play a significant role for firm survival. In the "intermediate" stage both age and productivity play a role in reducing firms' hazard rates.

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[a] *Corresponding author*. Department of Applied Economics II, Universitat de Valencia, Avenida de los Naranjos s/n, 46022, Valencia (Spain). E-mail: sesteve@uv.es.

[b] Department of Economics and Management, University of Trento, Via Vigilio Inama 5, 38122, Trento (Italy); email: fabio.pieri@unitn.it

[c] Department of Applied Economics II, Universidad Complutense de Madrid, Campus de Somosaguas, Madrid (Spain). E-mail: drodri@ccee.ucm.es

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1. Introduction

Despite the extended empirical literature on the determinants of firm survival,[i] and the well-developed body of research on the industry life cycle (ILC, hereafter), which analyzes industries' aging patterns in terms of entry and exit rates, number of firms, innovative activities and firm boundaries,[ii] there is little empirical evidence enlightening about whether and how surviving firms are qualitatively different at different stages of the evolution of an industry[iii] (Peltoniemi, 2011, p. 366).

This is unfortunate because, as time passes and industries evolve, firms go through different competitive stages: thus, the sources of competitive advantage and the characteristics that make a firm fit-to-survive may change through the stages of evolution of its industry.

This paper analyzes whether the role of firm age and firm productivity in firm survival changes across three different stages of the ILC. To this end, a representative sample of Spanish manufacturing firms with ten or more employees is employed, by taking advantage of the *Encuesta Sobre Estrategias Empresariales* (*ESEE*, hereafter)*,* a national survey on firm strategies sponsored by the Spanish Ministry of Industry since 1990. The dataset comprises information on 4,546 manufacturing firms from 1993 to 2009 and includes information on active firms of different ages.

The main contribution of this work is twofold. First, firms are assigned to three different stages of the ILC ("early", "intermediate" and "mature") by means of a composite indicator, which gathers several features of the industry they belong to. Four main industrial dimensions are taken into account, namely the prevalent type of innovation conducted within the industry (either product or process innovation), the number of incumbent firms, the number of product varieties introduced in the industry and the average degree of vertical integration of the firms belonging to the industry. Thus, this work departs from most of the previous empirical studies in the field (such as Gort and Klepper, 1982; Klepper and Graddy, 1990; Agarwal and Gort, 1996), which have defined the stages of an ILC in terms of net entry (or, alternatively, the number of active firms in the industry), by precisely

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[i] 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; Doms et al. (1995) has explored the role of firm technological capabilities.

[ii] See, among others, the seminal paper by Utterback and Abernathy (1975) and the formal model provided by Klepper (1996).

[iii] The relevant literature has indistinctly made use of the expressions "industry life cycle" and "product life cycle" to refer to the changing competitive setting in terms of entry/exit rates, number of firms, innovative activities and firm boundaries. Naturally, the term "industry" has a broader rendition than that of "product" and the interpretational issue has been also recognized by Malerba and Orsenigo (1996, p. 64) and Klepper (1997, p. 148, footnote no. 1). In this work, given that the indicator which identifies the stages of the life cycle has been defined at the 3-digit (NACE rev.2) level (see Table A.3 for the list of industries considered in this work), the expression "industry life cycle" and its "ILC" acronymic have been adopted along the entire text. The reader is cross-referred to Sections 2.1 and 3.2 for the definition of the stages of the ILC.

taking into account multiple (and not just one, i.e. the trend in the net entry rate) dimensions of the industry.

Second, this paper tests whether the role of firm age and firm productivity in firm survival differs across the different phases of the ILC. In this respect, this paper follows the extended tradition of applied work in innovation studies that take into account the existence of different regimes in which firms compete as industries evolve. Indeed, the early stage of the ILC may well correspond to what Winter (1984) and Audretsch (1991) call “entrepreneurial regime”, which is characterized by a type of innovative activities based on knowledge that is not of routine nature and aims at introducing radical product innovations, while the mature stage of the ILC corresponds to a “routinized regime” where the innovation activity is related to knowledge that mainly involves the optimization of the production process. Cost competition and economies of scale may gain relevance as the competitive setting move from the early stage to the mature stage of the ILC while, at the same time, quality and variety-driven competition may lose their relevance.

Thus, it is legitimate to ask whether older or more productive firms are always advantaged (in terms of lower risk of exiting the market) with respect to their younger or less efficient counterparts, or if their advantage is (to some extent) conditional on the particular stage of the ILC they are currently passing through.

The empirical analysis is carried out using survival methods: 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 “intermediate” and “mature” phases of the life cycle are lower than in the early phase. That is, firm survival chances differ across competitive regimes. This result is consistent with the theoretical prediction of the ILC literature, i.e. an initial turbulent phase characterized by a high firm turnover and “trial and error” behaviors by entrants, followed by more “stable” phases. Moreover, the role of firm age and firm productivity changes over the ILC. While firm age is negatively correlated with hazard rates in the “early” stage of the cycle, pointing out the role of “learning processes”, productivity does not help in explaining differences in firms’ risk of failure during this stage. Conversely, firm productivity is much associated with lower hazard rates in the “mature” stage of the cycle, when competition is primarily efficiency-driven, and firm age is not. In the “intermediate” stage both age and productivity play a role in reducing firms’ hazard rates.

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 shows and discusses the main results of the paper and includes a set of robustness checks. Finally, section 6 concludes.

2. Framework of analysis and related literature

A large body of research within the broad field of Industrial Dynamics (see Carlsson, 2016, pp. 12-13; p.19; among others) have examined the post-entry drivers of firm survival:[iv] these studies use information on the early years of life of a single cohort (or few cohorts) of entrants, following it over a short time span. Within the same field of research, the ILC tradition has instead focused on the "evolutionary" trajectory of particular industries (or products, by exploiting the available information at a finer level of disaggregation) from their inception to maturity.[v] The trajectory defines subsequent competitive stages featured by unlike (i) firms' entry and exit rates, (ii) number of competitors and product varieties, (iii) types of innovative activities and (iv) vertical boundaries of the firms. A way to "bridge the gap" between these two strands of the literature is to inquire into the drivers of firm survival across the stages of the ILC in order to check if the role played by key determinants, such as firm age and productivity, changes as the reference industry evolves.

Actually, several works have taken the stage of the ILC into account when studying the process of firm entry and the determinants of firm survival. By using data on 46 products contained in the *Thomas Register of American Manufacturers*, Gort and Klepper (1982) were able to identify five phases in those products' life cycle by considering the evolution in the yearly net entry rate over the long period 1887-1972. The approach and data employed in this seminal work (which have been adopted in few subsequent studies, mostly referring to the U.S. manufacturing)[vi] deserve, at least, two comments: (i) the information required (the net entry rate) is seldom available to researchers for (multiple) products not commercialized in the U.S. and during such long periods of time; (ii) entry and exit dynamics are employed as the unique identifiers for defining the stages of the ILC.[vii] Subsequent works have departed from the Gort and Klepper (1982) framework both in terms of the unit of analysis and the use of the net entry rate to identify the ILC stages.

As for the unit of analysis, many studies, have not focused on products but on industries (higher level of aggregation) and have covered shorter periods of time. For example,

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[iv] See, among others, the articles contained in the special issue of the *International Journal of Industrial Organization* (Vol. 13, Issue 4) regarding "The Post-Entry Performance of Firms", published in December 1995 (guest editors: David B. Audretsch and José Mata).

[v] Seminal studies in the ILC tradition aimed to identify and analyze the life cycle of specific products (approximately comparable to 5- or even 6-digit levels of disaggregation in a standard industry classification) in a historical perspective. For instance: Gort and Klepper (1982) developed a framework for analyzing 46 new products introduced over the last century, from commercial inception to 1972; Klepper and Graddy (1990) extended the time-series for those products until 1981; Klepper (2002) focused on four products only, i.e. automobiles, tires, televisions and penicillin.

[vi] Agarwal (1997) studied the role of firm size, growth and product diversification across five stages of the ILC, identified on the basis of information on entry rates. Agarwal and Gort (1996; 2002) applied the same procedure to study the role of learning-by-doing and endowments in firm survival across subsequent stages of the ILC. Agarwal and Audretsch (2001) studied the role of firm size in survival across two stages (formative and mature) of the ILC identified by using information on net entry rates. Agarwal et al. (2002) used the information on entry rates to define two stages (growth and maturity) of industries' evolution. All these works have made use of the information contained in the *Thomas Register of American Manufacturers*.

[vii] Interestingly enough, McGahan and Silverman (2001, p. 1156) claim that identifying the stages of the ILC via the inflection points in a long time series of the number of active enterprises (or by means of the analysis of the net entry rate) may generate remarkable difficulties in defining correctly the beginning and the end of the stages. For this reason, also other dimensions of an industry's evolution and different mechanisms for identifying the stages should be considered.

Tavassoli (2015) has used the information obtained from Statistics Sweden (SCB) on firm net entry rates and the Birch index of employment growth to identify three stages (“growing”, “mature” or “declining”) of the ILC to which fifty-nine 2-digit manufacturing sectors have been assigned. The author studies the changing role of a set of innovation determinants (namely, human capital, firm size, firms’ engagement in export and import activities and R&D expenditures) across the stages of the ILC.

As for the identification of the ILC stages, Audretsch (1987) used the information on the real output growth in all 4-digit industries in the U.S. to define three stages and to investigate how research intensity, human capital intensity and physical capital intensity vary along the life cycle of those industries. Audretsch and Feldman (1996) assigned more than two hundred 4-digit U.S industries to four stages of the ILC, based on the intensity and the promoter of innovation (i.e. small *versus* large firms) in order to study the propensity for innovative activity to spatially cluster as industries age. Maksimovic and Phillips (2008) have used the information on growth in shipments and the change in the number of firms at the 3-digit level to define four phases of the ILC (“Growth”, “Consolidating”, “Technological change” and “Declining”) for the sample of all manufacturing plants in the U.S. in the period 1972-1997. Otto and Fornahl (2010) identified “emerging” and “growing” regional clusters in the German media industry by means, respectively, of low and high values of the Concentration-Index (CI) proposed by Sternberg and Litzenberger (2004). Neffke et al (2011) studied the dynamics of agglomeration externalities along the ILC: in order to identify three stages of the life cycle for twelve 3-digit Swedish manufacturing industries in the period 1974-2004, the authors calculated a “maturity index” as the share of value added created by old plants over the total value added of the industry they belonged to in a particular year. Bos et al. (2013) adopted the same methodology proposed by Audretsch (1987) to assign twenty-one manufacturing sectors (either defined at 2-, 3- or 4-digit level) in six European countries to values of a continuous maturity index over the period 1980-1997.

All the works listed above share a characteristic that may potentially limit their analysis: they mainly take one dimension of industries’ “evolution” into account in order to define the stages of the ILC.

Conversely, the present work departs from them by building a composite indicator of the industrial ageing process which is based on four main industrial dimensions, i.e. the prevalent type of innovation conducted within the industry, the number of incumbents, the number of product varieties and the average degree of vertical integration of the firms belonging to the industry. Information in these dimensions come from the *ESEE* which is a yearly conducted survey collecting a representative sample of Spanish manufacturing firms with ten or more employees. The procedure followed to build up the composite indicator is explained in Section 3.2.

The use of a composite indicator in this paper is justified by two reasons. On the one hand, the methodology originally proposed by Gort and Klepper (1982) would not be feasible in this case: information on net entry rates is not available for the Spanish manufacturing industries since their birth to date. On the other hand, some extensive information on the dominant type of innovative activity conducted within an industry, the number of incumbents, the number of product varieties introduced in the industry, as well as information on the average sectoral degree of vertical integration are all available for the period 1993-2009 for forty-seven 3-digit (NACE rev.2) Spanish manufacturing industries.

Therefore, this paper adopts a procedure that takes multiple (and not just one) dimensions of an industry evolution into account (as suggested by Klepper, 1997 and McGahan and Silverman, 2001; among others) to assign firms to different stages of the ILC.[viii] Next section provides a detailed explanation of the approach used in this paper.

2.1. Identifying the stages of the ILC

One of the central issues within the ILC field of research is the identification of the stages of an industry's evolution. Steven Klepper clarified that:

> "[…] three stages of evolution [of an 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).

With respect to the previous works on the ILC, this paper adopts a novel approach and three stages of the ILC are identified by means of a composite indicator which recovers four relevant dimensions of the process of industries' ageing. The considered dimensions here follow.

1. *Predominance of product or process innovation in the industry*. The stages of the ILC are certainly dictated by the main type of innovative activity undertaken by firms (Filson, 2002, p. 97). Product innovation outweighs process innovation – both in terms of numbers of firms and intensity within each firm-- in early phases of the life cycle, where 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 the industry gets more mature (later stages) and price falls, cost-competition gets tougher and those firms that invest in process innovation (i.e. investments in product standardization and specialized equipment) improve their efficiency, survive and expand their market shares (Klepper, 2002).

2. *The extent of industry fragmentation*. In early stages of the ILC the number of competitors in the industry should be high: a high number of firms may act following "trial and error" strategies. However, as time passes and price decreases, the advantage

[viii] Nonetheless, it is acknowledged that the lack of information on both net entry rates and the entire history of specific products may be a limitation for the scope of the present work.

of being an incumbent (in terms of production costs) could become insurmountable and the entry process may virtually stop (Gort and Klepper, 1982; Klepper, 1996). The most efficient firms may prevent (less efficient) potential competitors from entering the market. Consequently, the number of firms declines making the industry more concentrated in the late phases of the ILC.

3. *The number of product varieties*. Before the advent of a dominant design[ix] (Suarez and Utterback, 1995), some fierce competition takes place by experimenting a large variety of products, each one produced at a low scale (Malerba and Orsenigo, 1996). The emergence of a dominant design marks the transition to the mature stage of an industry. Thus, in the late stages of the ILC a lower number of product varieties are provided in the industry, i.e. product diversity decreases.
4. *The average degree of vertical integration*. In the early phases of a ILC, the final market is smaller and there is less room for division of labor and specialization (Stigler, 1951, p. 190). An organized market for intermediate inputs and services would not be developed yet, and the "average" firm in the industry would resort to internal production to fulfill its demand of intermediates and co-ordinate its production process. Thus, in early stages of the ILC, the average degree of vertical integration within the industry should be, *ceteris paribus*, higher than in later stages (Klepper, 1997, p. 152).[x]

Proxies for these four dimensions are built up relying on the information available in the *ESEE* survey. After having operationalized these dimensions in an intuitive way, in Section 3.2 we develop a summary indicator of the ageing stage of the industry a firm belongs to, which is based on the co-occurrence of them.

Next section is devoted to discuss the expected effect of age and productivity on firm survival across different competitive stages of the ILC.

2.2. Age and productivity as determinants of firm survival over the ILC

Little is known about how drivers of firm survival change (gaining or losing relevance) as an industry ages (Peltoniemi, 2011, p. 366): this paper fills this gap by focusing on the role played by two important drivers, i.e. firm age and firm productivity.

Firm age is a proxy for the "learning" processes that take place within the firm as time passes (see Arrow, 1962; Jovanovic, 1982; Ericson and Pakes, 1995, among others). It has

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[ix] 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".

[x] However, the idea that the evolution of the vertical structure of the firm in an industry depends only on the extent of the market and the attendant division of labor may not hold in all industries. Indeed, Helfat (2015, pp. 808-811), furnishes some explanations of why Stigler's hypothesis does not apply in all cases: the evolution of the vertical structure of a firm depends on several factors that Helfat points out as "contextual (to the industry) factors". For example, the type of innovation, either "systemic" (i.e. which needs a strong coordination and alignment among the stages of the innovation process) or "autonomous" (i.e. which may be undertaken in its different stages by different agents) plays a role for firms at an industry's inception in their choice of being, respectively, vertically integrated or not. Thus, the choice made in this work ought to be considered as a simplification (based on Stigler's hypothesis) that is functional to the identification of the different stages of the ILC.

been found that older firms have an advantage over their younger counterparts due to their accumulated "experience".[xi] However, the advantage of older and more experienced firms may be related to the stage of the life cycle of the industry they belong to. The positive role of age in explaining firm survival may be mitigated in the mature stage of the ILC for different reasons.

On the one hand, this may happen because of the higher relevance of "trial and error" experimentation (and learning-by-doing) in terms of both the technology adopted and the innovation conducted by the firms in the earlier stages of the ILC (see Klepper, 1997, p. 149; Agarwal and Audretsch, 2001, p. 26). On the other hand, it may also be due to the lower amount of young firms entering the industry as it becomes mature: at later stages of the ILC --given the tougher price competition -- only the most productive (and innovative) firms may enter the market, thus leading to a lower rate of failure of young firms with respect to coetaneous firms in other stages of the ILC (Klepper, 2002). The following hypothesis can thus be put forward:

> **Hypothesis 1-** *Older firms enjoy an advantage (in terms of lower hazard rates) with respect to their younger counterparts and this relationship is stronger in the "early" stage of an industry's life cycle.*

Productivity has been found to be a relevant driver of firm survival (Griliches and Regev, 1995; Foster et al. 2001; Dosi, 2012): long-run selection operates via elimination of the least productive firms.

However, firm efficiency may be particularly relevant for survival in mature stages of the ILC. In fact, in these stages, tougher price competition forces firms to compete not on quality or variety but on decreasing the average costs for producing the standardized (and dominant) product via investments in better production processes and special purpose machinery (Malerba and Orsenigo, 1996, p. 63). The typical competitive setting of the mature stages of the ILC is a "routinized regime" where the innovation activity is related to knowledge that mainly involves the optimization of production processes, thus providing the most efficient firms with a clear survival advantage. Thus, a second hypothesis can be put forward:

> **Hypothesis 2-** *More productive firms have an advantage (in terms of lower hazard rates) with respect to their less productive counterparts, and this relationship is stronger in the "mature" stage of an industry's life cycle.*

[xi] In the "passive" learning model by Jovanovic (1982), firms become more conscious about their unknown type (level of efficiency) as time passes and adjust their growth rates with the updated expectation about their type. In "active" learning models (Ericson and Pakes, 1995), a firm's type can be partially modified through purposive investments in the development of new technologies. In both models, firm age 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.

3. Data and descriptive analysis

3.1. Data: the ESEE survey

Information used in this work has been taken from the *ESEE*, which is an annual panel survey of Spanish manufacturing firms sponsored by the Ministry of Industry (*Ministerio de Economía, Industria y Competitividad*) and carried out since 1990. The survey excludes firms with less than 10 employees; firms between 10 and 200 employees are initially selected by randomly sampling in each industry (at the 2-digit NACE rev.2 level) 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 information provided by the survey has a panel structure.[xii] Overall, the dataset is an unbalanced panel of 4,546 firms over the period 1993-2009.

The survey provides rich information on firm characteristics and strategic choices in terms of innovative activities, information on products and competitors, firms' sub-contracting activities, advertising and internationalization strategies: this firm-level information has been exploited and summarized at the industry-level in order to identify the stages of the ILC. The survey also provides information on both the date of market entry (date of birth) and the date in which a firm first comes under observation. Finally, the survey includes information on whether a firm stays in the market, exits the market or leaves the survey.[xiii] For the purpose of this work, a firm is defined as "exiting the market" in period *t* when that is the last year in which the firm stays in the market.[xiv]

3.2. Empirical approach to identify the stages of the ILC

As mentioned in Section 2.1, the identification of the stages of the ILC is based on a composite indicator which gathers four dimensions of an industry's evolution. These dimensions are measured using the information contained in the *ESEE* at the firm-level, which has been aggregated at the industry-level for forty-seven 3-digit (NACE rev.2 classification) Spanish manufacturing sectors in the period 1993-2009.[xv] Thus, as for the unit of analysis, this work focuses on "placing" industries along their life cycle similarly to Neffke et al. (2011) and Bos et al. (2013).

The first dimension is the predominant type of innovation activity (either product or process innovation) conducted within an industry in a given year. The available dichotomous information on whether firm *i* has introduced (at least) one product and/or one process innovation (or nothing) in each year *t* is our *terminus a quo*. Based on this

[xii] Efforts have been made to minimize attrition and incorporate each year new firms with by following the same criteria used in the base year. This helps in maintaining the representativeness of the sample over time (see http://funep.es for further details).
[xiii] Note that the ESEE is not a mandatory survey.
[xiv] Therefore, information in 2010 is used to identify those firms exiting in 2009.
[xv] For the list of the industries considered in the empirical analysis the reader is cross-referred to Table A.3.

information, we calculate the ratio of the number of firms having introduced at least 1 product innovation to the number of firms having introduced at least 1 process innovation in industry m in year t, $\mathrm{TINNOV_{m,t}}$.[xvi] The subscript m refers to the industry the i^{th} firm belongs to, while t refers to the year. Then, $TINNOV_{m,t}$ is normalized between 0 and 1, by dividing the value of the variable for the m^{th} industry in year t by the maximum value among all industries in the same year.

The second dimension is the degree of market fragmentation. The variable is built starting from the yearly information about the number of incumbents that firms face in their relevant market.[xvii] The initial information is a categorical variable whose value depends on the number of competitors faced by firm i. This variable may take four different values: it is equal to 1 when the number of competitors is lower than 10; it takes value 2 if that number is between 10 and 25; it is equal to 3 if competitors are more than 25; it takes value 4 when the firm reports that it is active in an "atomized" market. Thus, the variable $\mathrm{FRAG_{m,t}}$ is built as the average value reported by all firms belonging to industry m in a given year: a value close to 4 suggests that firms belonging to industry m in year t face a more "fragmented" market, while a value close to 1 corresponds to a concentrated structure. As the other variables capturing the evolution of the life cycle, the variable is normalized between 0 and 1 , by dividing the value of the variable by the maximum value among all industries in the same year.

The average propensity for the firms in industry m to introduce new product variants, $PVAR_{m,t}$, is the third dimension of the ILC that is taken into account. $PVAR_{m,t}$ measures the percentage of firms that, in industry m and year t, have introduced new product variants, based on the dichotomous information available at the firm-level in the ESEE survey. This variable is normalized between 0 and 1 (as previously explained), similarly to the other variables capturing the evolution of the life cycle.

Finally, the average degree of vertical integration within the m^{th} industry in year t, $\mathrm{VINT_{m,t}}$, is measured as the reciprocal of the average share of intermediate inputs sub-contracted by all firms belonging to the industry to their subcontractors in a given year. The variable is normalized between 0 and 1, by dividing the value of the variable by the maximum value among all industries in the same year.

It is worth pointing out that the variables measuring the four dimensions of an industry's evolution are calculated as five-year moving averages in order to control for undesirable fluctuations due to errors in the measurement of some of the variables in a given year which have nothing to do with the stage of the ILC, and to control for business cycle volatility, as suggested by Neffke et al (2011, p. 55). For example, the value assigned to

[xvi] A firm which in a given year has introduced both a product and a process innovation adds 1 observation to the numerator and the denominator of the $TINNOV_{m,t}$ variable. The percentage of innovative firms (which are about 45% of all firms contained in the *ESEE*) that simultaneously introduce product and process innovations is about 35%**.**

[xvii] Actually, the concept of "relevant market" is narrower than that of "industry" defined at the 3-digit level. Firms surveyed by the *ESEE* are asked to provide their view on the real number of competitors they face in their relevant market. Thus, a market is the effective *locus* of competition for the firms, while the industry gathers all firms sharing a common technology and similar production processes.

$TINNOV_{m,t}$ in 1993 is the average value of the variable referring to industry *m* over the period 1991-1995. Then, for each year *t*, the ILC indicator is calculated as the arithmetic mean of the four dimensions:

$$ILC_{m,t} = (0.25) \cdot TINNOV_{m,t} + (0.25) \cdot FRAG_{m,t} + (0.25) \cdot PVAR_{m,t} + (0.25) \cdot VINT_{m,t} \quad (1)$$

The indicator is industry-specific and it changes each year (i.e. it is yearly time-variant) for all firms belonging to the same 3-digit industry (as advised by Bos et al., 2013; p. 82): nonetheless, its temporal variation is smoothed through the application of the 5-year moving average to all its four components. Values of the indicator close to 1 (0) characterize those industries passing through an "early" ("mature") stage of the ILC.[xviii]

In order to gain further insights into the $ILC_{m,t}$ indicator, Table 1 reports some preliminary statistics. Although the specific values of the indicator are of little interest *per se*, its distribution gives an idea of the relative positioning of the bulk of industries considered with respect to this indicator, which ranges from 0 to 1. Actually, even though some industries in some years show relatively high values of the $ILC_{m,t}$ indicator (the top 10% shows values higher than 0.75), most of the observations are concentrated around intermediate values of the indicator. Indeed, around 50% of industry/year pairs are characterized by values of $ILC_{m,t}$ below 0.6. This might suggest that many Spanish industries are currently passing through "intermediate" stages of their life cycle.

[INSERT TABLE 1 ABOUT HERE]

Similar conclusions can be reached from Figure 1, which depicts the distribution of the $ILC_{m,t}$ indicator.

[INSERT FIGURE 1 ABOUT HERE]

After having calculated the $ILC_{m,t}$ indicator at the industry-level, two further steps are necessary. First, in order to determine the stage of the life cycle an industry is passing through, the distribution of the $ILC_{m,t}$ indicator is "cut" into three parts in each year *t*: the top 25% of observations are assigned in that year to the "early" stage of the life cycle and the bottom 25% to the "mature" stage; the remaining observations are assigned to the "intermediate" stage. Second, each firm *i* in year *t* is assumed to pass through the ILC stage of the 3-digit industry it belongs to. In this way, as previously said, the $ILC_{m,t}$ indicator is yearly time-variant and industry-specific: all firms belonging to a given 3-digit industry will be assigned to the same stage of the ILC in a given year.

A first test on the ability of the $ILC_{m,t}$ indicator to capture the stage of the ILC an industry is currently passing through can be done (in line with Bos et al. 2013, p. 83) by calculating the average value of the indicator over the entire period 1993-2009 and by grouping the 47 industries into "high-tech" and "low-tech" industries (the reader is cross-

[xviii] Table A.1 in the Appendix A displays the Pearson correlation coefficients between all pairs of the four dimensions of the ILC. These variables capture different dimensions of the ILC.

referred to Table A.3, where the list of the industries considered in the analysis and the adopted taxonomy in terms of technological intensity is explained). It is reasonable to expect high-tech industries to be associated with a higher average value of the indicator (corresponding to "early" stages in the ILC), while low-tech industries to a lower average value of the indicator (corresponding to more "mature" stages). This is confirmed by the results shown in Table 1, where high-tech industries show an average value of the $ILC_{m,t}$ indicator equal to 0.614, while low-tech industries show an average value equal to 0.572.

Furthermore, it is worth examining the pattern of variability of the $ILC_{m,t}$ indicator. Each industry may take multiple values of the indicator in the period 1993-2009, possibly making transitions from one stage of the life cycle to another one. The ILC framework would predict that, from *t-1* to *t,* most of the industries either persist in the same stage or move forward to following stages.[xix] Table 2, which contains the yearly transitions from one stage to another, confirms this prediction: most industries persist in their initial stage and forward transitions (i.e. from "early" to "intermediate" and from "intermediate" to "mature") are more frequent than backward transitions (from "intermediate" to "early"), the only exception being a relative higher percentage of industries moving from the "mature" stage to the "intermediate" one. Overall, a relatively small share of industries undergo backward transitions (i.e. they move to earlier stages of the ILC).

[INSERT TABLE 2 ABOUT HERE]

Despite their low incidence, the cases of backward transition deserve further comments. Abernathy et al. (1983), by referring to the U.S. producers of automobiles, label these cases as episodes of "de-maturity": in their framework, these transitions are due to a significant change in the competitive environment that incumbents face. New firms enter the market with fresh ideas (new products and new ways of organizing and coordinating the production process), which may lead to a further increase in the number of active firms, an increase in terms of product varieties, a resurgence in product innovation and changes in the division of labor among firms. If one or more changes of this kind are captured by the four dimensions of the $ILC_{m,t}$ indicator, backward transitions to earlier stages of the life cycle may be observed. Klepper (1997, pp. 158, 160, 175) points out that the change in the competitive environment leading to a backward transition may be due to different causes not fully considered by the ILC framework. First, the entry of foreign competitors in the market may lead to the introduction of new technologies and a consequent increase in product innovation.[xx] Second, the possibility for later entrants of establishing market niches characterized by a customized demand may lead to the introduction of new product variants and the reduction in the relevance of efficiency-driven competition. Third, the uncertainty in the final market may lead experienced firms in the "mature" stage of the ILC

[xix] That is, from "early" to either "intermediate" or "mature", and from "intermediate" to "mature".

[xx] A classic example is the major entry made into the market shares of the U.S. leaders by foreign producers of smaller cars (such as Toyota and Volkswagen) during the 1960s.

to vertically re-integrate in order to be able to better react to changes in customers' needs in terms of product functionality and design (see Helfat, 2015, pp. 4, 6).[xxi]

We can conduct a descriptive analysis on the cases of industry "de-maturity". Indeed, Table 3 provides a comparison between two groups of firms: those belonging to industries which have experienced a backward transition from year *t-1* to year *t* ("de-mature industries") with the rest of firms in the sample (both firms in industries which are persistent in the same stage and those which have experienced a forward transition from year *t-1* to year *t*). Three dimensions are considered: first, the extent of foreign competition proxied by the import share (i.e. imports-to-sales ratio); second, the degree of demand customization measured by a dummy variable that takes value one when the products are customized and zero when they are standardized; third, the degree of uncertainty in the final market, which has been measured as proposed by Lieberman (1991).[xxii] These two groups of firms differ in two out of three dimensions considered. In line with our expectations, firms that belong to industries which have experienced a backward transition face, on average, a stronger international competition and have to deal with more uncertainty in the final market than their counterparts (Abernathy et al., 1983; Klepper, 1997); conversely, at odds with our expectations, they do not show a higher degree of product customization with respect to the other firms.

Even recognizing the descriptive nature of both this last check on the characteristics of firms belonging to "de-mature" industries and the previous one on the correspondence between the values of the $ILC_{m,t}$ indicator and the level of technological intensity in the industry, the composite indicator seems to recover rather well the main features of the process of industrial evolution across the three stages of the life cycle.

[INSERT TABLE 3 ABOUT HERE]

The following Section describes how firm age and productivity have been defined and included in the empirical analysis in order to examine their role in firm survival over the three stages of the ILC.

3.3. Firm age and firm productivity over the ILC

Firm age and firm productivity are introduced in the empirical model as vectors of dummy variables (i) because of easiness of interpretation and (ii) to capture a possible non-linearity

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[xxi] Christensen et al. (2002, pp. 972-975) discuss the case of the 2.5-inch disk-drive industry during the 1990s as an example of vertical re-integration performed by the most technological experienced firms, such as IBM, Toshiba, Hitachi and Fujitsu to manage complex and interdependent technologies in order to cope with a large dissatisfaction for notebook computers in terms of disk-drive capacity, weight and power consumption.

[xxii] Following Lieberman (1991), uncertainty is measured as the average of squared residuals of the following regressions

$$y_{im,t} = \gamma_0 + \gamma_0(t) + \gamma_0(t^2) + \gamma_0(t^3) + v_{im,t}$$

where $y_{im,t}$ is (the log of) the real output (i.e., deflated by firm-specific price variations), *t*=1,…,17 is an integer increasing by one in each year and *m*=1,…,47 refers to the industry.

in their association with exit chances. Both vectors have been built starting from time-varying variables, thus allowing for possible changes in their effects over time.

The age of the *i^th^* firm is calculated as the difference between year *t* and the year of establishment of the firm. The taxonomy adopted by Barba Navaretti et al. (2014) is employed and firm age enters the econometric model as a vector of *(j-1)* dummy variables, AGE_j, where:

$$j = \begin{cases} 1 \ if \ 0 < AGE_{i,t} \leq 10 \\ 2 \ if \ 10 < AGE_{i,t} \leq 20 \\ 3 \ if \ 20 < AGE_{i,t} < max \end{cases} \tag{2}$$

The level of productivity of the i^{th} firm in year *t* is calculated as real labor productivity, i.e. the ratio of gross value added at constant (1990) prices to total employment. After having calculated the value of productivity at the 25th and 75th percentile of its distribution in each year, we introduce the variable in the econometric model as a vector of *(p-1)* dummy variables, $PRODUCTIVITY_p$, where:

$$p = \begin{cases} 1 \ if \ PRODUCTIVITY_{i,t} \leq PRODUCTIVITY_t^{25th} \\ 2 \ if \ PRODUCTIVITY_t^{25th} < PRODUCTIVITY_{i,t} \leq PRODUCTIVITY_t^{75th} \\ 3 \ if \ PRODUCTIVITY_{i,t} \geq PRODUCTIVITY_t^{75th} \end{cases} \tag{3}$$

Both vectors of dummies have been introduced in the empirical model as one year lagged in order to reduce potential simultaneity issues.[xxiii]

Moreover, to minimize the risk of capturing spurious correlations, a vector of control variables has been introduced in the empirical model. As firm age and productivity, all controls have been built as categorical variables and they have been introduced in the empirical model as one year lagged variables. The vector of controls includes measures of: *firm size* (two categories, small --i.e. less than 50 employees-- and large firms); *firm growth* (continuous variable, calculated as the 1-year percentage variation in the number of employees); *firm profitability* (three categories, low-, medium- and high-profitable firms), *firm R&D intensity* (three categories, low, medium or high, based on the share of employees involved in R&D tasks), a dummy variable identifying *multi-plant firms* and another one identifying firms owned by *foreign investors*. Finally, a vector of eight 2-digit industry dummies (see Table 5) have been included in the empirical model to control for the unobserved and time-invariant factors which may be correlated with both firm survival and its determinants.

A detailed explanation of the control variables is included in the Appendix A. Table A.2 reports the matrix of Pearson's correlation coefficients between all pairs of independent variables included in the econometric analysis.

[xxiii] Table 9 in Section 5.3 shows that the main results of the paper do not change significantly when both age and productivity are included as continuous variables.

3.4. Descriptive analysis

Table 4 compares firms' characteristics across the stages of the ILC: firms belonging to industries passing through different stages sharply differ in several dimensions. On average, firms in the "early" stage of the ILC are younger, smaller, less productive and less profitable than their counterparts in "intermediate" and "mature" stages. Besides, firms in the former stage employ a higher share of employees in R&D activities than those firms passing through the "mature" stage of the ILC (even if firms in the "intermediate" stage are those with the highest share of employees involved in R&D activities). Moreover, firms that compete in the "mature" stage of the ILC are more frequently multi-plant and partially owned by foreign investors than those in the "early" stage of the ILC. Standard deviations for each firm characteristic are reported in brackets and show that the variation in firm characteristics within each stage is comparable to the variation observed within the entire sample ("All stages"). This is relevant for the identification of the effects exerted by age and productivity on firm survival within each stage of the ILC.

[INSERT TABLE 4 ABOUT HERE]

Given that firms in the "early", "intermediate" and "mature" stages of the ILC are different in several dimensions, it is necessary to conduct a multivariate econometric analysis to assess the role played by age and productivity in firm survival when the moderating effect of other firm characteristics is taken into account. This will be the focus of Section 4.

4. The empirical model

Survival methods are employed to evaluate the differential role played by firm age and firm productivity across different competitive stages: the dependent variable is the hazard rate, that is, the probability of firm exit in a given period conditional on survival up to that period. Some properties of the empirical model are worthy to point out. First, survival methods allow controlling for both the occurrence and the timing of firm exit. Second, they appropriately deal with right-censoring, that is, those cases where the only known information is that a firm has survived up to a given period. Third, they easily handle time-varying covariates, which is interesting since survival is related to the ability of a firm to adapt to a changing competitive environment. Fourth, they are suitable to control for the presence of unobserved firm heterogeneity that may lead to biased inference.

This paper uses discrete-time survival methods given the nature of the data contained in the survey. Although firm exit may occur at any particular instant in time, the ESEE survey provides yearly information. Given that, survival times are grouped into discrete intervals of 1 year (interval-censored data). The discrete time hazard function (or probability of ending the spell in *t* periods conditional on survival up to *t-1* periods) can be written as:

$$h_i(t) = \Pr(t-1 < T_i \leq t | T_i > t-1) = \frac{\Pr(t-1<T_i\leq t)}{\Pr(T_i>t-1)} \qquad (4)$$

In order to assess the role played by firm age and firm productivity in firm survival, a complementary log-log model (*cloglog*) is estimated. In particular, we estimate a discrete-time version of the Cox proportional hazard model.[xxiv] By assuming that the discrete hazard rate follows a complementary log-log distribution (Prentice and Gloeckler, 1978) and allowing for unobserved individual heterogeneity, the estimated equation takes the following form:

$$\boldsymbol{cloglog}[\mathbf{1} - h_t(AGE_j, PRODUCTIVITY_p, X|v)] \equiv$$

$$\equiv \boldsymbol{log}(-\boldsymbol{log}[\mathbf{1} - h_t(AGE_j, PRODUCTIVITY_p, X|v)]) = \beta'_{1j}AGE_j + \beta'_{2p}PRODUCTIVITY_p + \boldsymbol{\delta}'\boldsymbol{X} + \boldsymbol{\gamma_t} + \boldsymbol{u} \qquad (5)$$

where $\boldsymbol{\gamma_t}$ is the interval baseline hazard and summarizes the pattern of duration dependence --which is parameterized with a set of 17 year dummies (1993,…, 2009)—and X is the vector of control variables.

The most interesting parameters are β_{1j} and β_{2p}, as they capture the conditional associations of age and productivity with the firm hazard rate. The baseline hazard (when $AGE_j, PRODUCTIVITY_p, and\ X$ are all equal to 0) varies over years and the effect of covariates is constrained to be a constant (over duration time) proportional shift of the baseline hazard function common to all spells.

Firm-level random effects are also included by means of an error term $u = \log(v)$ that is assumed to be normally distributed with zero mean and σ^2 variance:[xxv] the frailty term allows one to control for unobserved individual heterogeneity. To obtain efficient estimators and unbiased standard errors, we apply the robust (Huber-White sandwich) estimator.

For the specification in Equation 5 it is the ordering of exit times that matters, rather than the actual times by themselves. This is another important feature of the empirical model, given that the analysis is based on calendar time: the baseline hazard function controls for the overall evolution of risk common to all firms in the market during a particular year and firm age may be well included in Equation 5 as an independent variable.

5. Econometric results

This Section reports the results of the estimation for different specifications of Equation 5. Before introducing the main results, it is worth pointing out some features of the empirical model and some guidelines for the interpretation of coefficients.

First, in order to control for the presence of firm-level unobserved heterogeneity, frailty survival models are estimated. The null hypothesis of no unobserved individual heterogeneity cannot be rejected at significance level of 0.01. Hence, the non-frailty models are the appropriate models to be estimated. Second, all estimates in the tables

[xxiv] See Jenkins (2005) for an excellent overview of complementary log-log and proportional hazards models.

[xxv] The test regarding whether the variance of the frailty term is statistically different from zero is performed in Section 5: if this variance is not statistically different from zero, a non-frailty model will be the preferred specification. Under the null hypothesis, the statistic is distributed as a chi-squared with one degree of freedom.

contain *hazard ratios*. The coefficients indicate the effect on the hazard for a shift from 0 to 1 for a dummy variable or a one-unit increase in a continuous variable. Thus, a hazard ratio smaller (greater) than one indicates a reduction (increase) in the hazard and a longer (shorter) duration. A hazard ratio equal to one indicates no effect on the hazard by the considered independent variable. The main results are reported in Tables 5 and 6.

5.1 Firm survival and the ILC

Table 5 shows a set of specifications in which the vector of dummy variables capturing the different stages of the ILC are included as regressors ("pooled" results). Two out of three corresponding dummies are included, taking the "early" stage as the baseline/omitted category. $STAGE_{INTERMEDIATE}$ and $STAGE_{MATURE}$ capture the differences in terms of hazard rates across the three competitive stages when assuming firm characteristics (age, productivity and controls) to have the same effect across them. In the next sections this assumption will be relaxed in order to check whether or not firm age and firm productivity play different roles in firm exit across the three stages of the ILC.

[INSERT TABLE 5 ABOUT HERE]

Column 1 of Table 5 shows the results when including the vector of year dummies only. Results are not very informative *per se* and capture the role of the business cycle. The risk of firm exit was higher in 1993-1994, 2002 and 2007-2009.

Column 2 reports more interesting results, showing the different hazard rates characterizing observations belonging to each stage of the ILC: in particular, those firms belonging to industries which are passing through "intermediate" and "mature" stages show lower hazard ratios than their counterparts in the "early" stage. This result is consistent with the ILC framework that suggests the existence of a first turbulent phase characterized by a high turnover of firms that employ an array of exploratory techniques and a high degree of uncertainty on product design and consumer demand; after this stage, the market starts to become more stable.

Column 3 shows the role of firm age in firm exit, conditional to the stage of the ILC. Firm age, as expected (Freeman et al., 1983; Mata and Portugal, 1994; Mata et al., 1995), shows a clear negative relationship with the risk of exit, with older firms (those which are active since more than 20 years) showing a hazard rate which is more than 40% lower than that faced by the youngest (baseline and omitted) group of firms.

When the measure of productivity is introduced (Column 4) some interesting results emerge. First, more productive firms (especially those in the highest group of productivity, $PRODUCTIVITY_{H}$) show a sizeable and significant lower risk of exit than the one shown by their least productive counterparts (Griliches and Regev, 1995; Foster et al. 2001; Dosi, 2012). 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 showing, on average, higher levels of productivity. Third, once we add the control for firm productivity, $STAGE_{INTERMEDIATE}$ and $STAGE_{MATURE}$ lose part of their explanatory power for firm exit (their coefficients become slightly higher, i.e. closer to 1). The latter result is rather interesting and –to some extent-- in line with previous works in the ILC field of research: as one moves from the "early" to the "mature" stage of the ILC, market competition becomes more efficiency-driven, with firms forced to compete by lowering their average costs. As pointed out by Klepper (1996), more productive and large firms may enjoy an advantage as they can spread process innovations (and their potential benefits in terms of lower costs) over a larger scale. Hence, differences in productivity between firms that are active in the "early" (baseline and omitted stage) and "mature" stages may capture a relevant part of the gap in hazard ratios between them.

Finally, when the full vector of controls is included in the empirical model, the difference in terms of hazard ratios between the "early" and "intermediate" stage becomes smaller. The "mature" stage again shows the lowest hazard ratio among the three stages, which points out that it is a relatively "stable" stage of the life cycle. *Ceteris paribus*, the most productive firms and those from 11 to 20 years old show the lowest hazard ratios.

The coefficients referring to the control variables deserve some comments. More profitable firms (medium-profitable, $EBITDA_M$, and high-profitable, $EBITDA_H$) show lower hazard ratios than their less profitable counterparts ($EBITDA_L$, omitted category), in line with previous works (see Bellone et al., 2008, among others). Firms that have larger shares of the workforce employed in R&D activities ($R\&D_M$ and $R\&D_H$) show lower hazard ratios than that shown by their counterparts (Kim and Lee, 2011) and the advantage is especially strong for those firms characterized by a medium R&D intensity, possibly pointing out the risky nature of R&D activities. Smaller firms ($SIZE_M$) do not show a statistically significant higher hazard ratio than their larger counterparts but those firms that have grown more in the previous year do show a much lower hazard ratio than their counterparts: growth is key to survive.[xxvi] Multi-plant firms show lower hazard ratios than their single-plant counterparts, while (partially) foreign-owned firms show higher hazard ratios than the reference category: however none of the two coefficients is statistically significant and this may due to the large vector of controls included in the analysis and the possible cross-correlations among them.

5.2 The role of firm age and productivity across different stages of the ILC

It is worth further investigating whether the role played by firm age and firm productivity differs across the three stages of the ILC. To do that, it is necessary to estimate a separate regression for each stage: results are reported in Table 6.

[xxvi] Interestingly enough, when the lagged growth rate is not included in the analysis, the higher hazard ratio of small firms corresponds to a statistically significant, and higher than 1, coefficient. This may well be the result of the statistical relation between firm size and firm growth.

[INSERT TABLE 6 ABOUT HERE]

In Column 1, when we include firm age with no additional explanatory variables, the oldest firms (*AGE_3*) show lower hazard rates than their younger counterparts, but this effect is not statistically significant in the “mature” stage of the ILC. This may be the result of multiple causes, such as the higher relevance of learning-by-doing, the higher amount of “trial and error” strategies adopted by the firms in attempting to introduce new variants of the (still not standardized) product and, finally, the higher amount of young firms entering the market in the “early” stage of the ILC which corresponds to what the innovation literature would refer to as an “entrepreneurial regime” (Winter, 1984; Audretsch, 1991).

When productivity is introduced in the empirical model (Column 2), age loses part of its explanatory power in explaining firm exit. However, this is less pronounced in the “early” stage of the ILC where firm age continues to be very significant while being very productive ($PRODUCTIVITY_H$) seems not to explain a lower risk of firm exit. The most productive firms result to be characterized by lower hazard rates (even 70% lower) than the least productive ones in both the “intermediate” and “mature” stages.

Column 3 of Table 6 reports the estimates when the full vector of controls is introduced in the regressions. The results are confirmed and, to some extent, even strengthened. The roles of firm age and firm productivity are almost “polarized” in the two extreme stages of the ILC. On the one hand, firm age is not relevant in explaining different firm exit probabilities during the “mature” stage, but it plays a relevant role in the other competitive stages (“early” and “intermediate”). On the other hand, during the “mature” stage firm efficiency turns out to be the crucial variable for survival (Klepper, 1996). Admittedly, the most efficient firms still retain some advantage also in the “intermediate” stage of the ILC, where both age and productivity play a role in reducing firms’ hazard rates.

Therefore, our results confirm both Hypotheses 1 and 2 contained in Section 2.2. We further explore the potential interaction effect played by firm age and firm productivity throughout the three competitive stages in Table 7.[xxvii]

[INSERT TABLE 7 ABOUT HERE]

The value in each cell has to be interpreted as the interaction played by age and productivity categories with respect to the omitted group (i.e., the interaction between the categories AGE_1 and $PRODUCTIVITY_L$). Some interesting evidence emerges. On the one hand, in both the “young” and the “intermediate” stages of the ILC, firms aged between 11 and 20 (AGE_2) enjoy better survival prospects, whatever the level of productivity considered. On the other hand, the results in Table 7 confirm that age shows a little impact on firm survival in the “mature” stage. Indeed, in this phase, for any productivity level, differences in survival chances across different age groups are small. Finally, whatever the

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[xxvii] We thank an anonymous referee for having suggested to further explore the interaction effect of firm age and productivity on firm survival.

age category under consideration, the risk of firm exit decreases as firm productivity increases in all the stages of the ILC. Overall, from this post-estimation analysis, it is clear that productivity is crucial for firm survival and it seems to be even more relevant than firm age. Actually, the interaction effect of age and productivity on firm survival across the stages of the ILC may be also affected by discontinuities in technical change, whose relevance across industries is heterogeneous (see Perez, 2010, for a general analysis on discontinuities in the process of innovation).

As for the other control variables, more profitable firms maintain their advantage in terms of lower hazard ratios with respect to their less profitable counterparts across all three stages. Firms characterized by a higher R&D intensity maintain their advantage with respect to their less-intensive R&D counterparts but the effect is significant in the "early" stage of the ILC only. Firms that have grown more in the previous time period show a significant advantage in terms of lower hazard ratio, and this relationship is stronger in the "mature" stage of the ILC: in this stage, growing enough to reach a minimum efficient scale may be fundamental to survive. The other controls (*MULTIPLANT, FOREIGN*) maintain the signs found in the "pooled" estimation (Table 5) but they are statistically significant only in some specific stages.

All in all, our results suggest two interesting insights: (i) firms' survival conditions differ across the stages of the life cycle of the industry they belong to; (ii) the role of firm age and firm productivity is different for explaining firm survival across the different stages of the ILC.

5.3 Robustness checks

This section provides several supplementary empirical results as robustness checks.

First, we examine whether a different allocation criterion of industries to the stages of the life cycle produces significant changes in the estimates. To this end, industries are assigned to the stage of the ILC in terms of equi-populated groups, i.e. bottom, middle and top terciles (33% each) of the distribution of the $ILC_{m,t}$ indicator instead of (bottom) 25%, (middle) 50%, (top) 25%. The results presented in Table 8 are fairly consistent with those reported by Table 6.

[INSERT TABLE 8 ABOUT HERE]

Second, we investigate whether an alternative definition of the main explanatory variables change the main results. Specifically, we now include firm age and firm productivity as continuous variables (in natural logarithms) instead of categorical variables. Although the latter makes it easier and more intuitive the interpretation of hazard ratios estimates allowing for simple comparisons, the adopted approach may lead to some loss of information. Consequently, Table 9 shows that when age and productivity are included as continuous variables in the empirical model, results are in line with those reported in Table 6. While firm productivity shows a coefficient lower than one which is mostly significant in the "mature" stage of the ILC (pointing to a lower risk of firm exit for the most productive firms), firm age shows a coefficient lower than one in the "early" stage of the ILC, even if not statistically significant.

[INSERT TABLE 9 ABOUT HERE]

Third, the analysis is replicated by separately considering each of the four dimensions of an industry's evolution, instead of using the composite $ILC_{m,t}$ indicator. The use of a composite indicator may well synthesize the co-occurrence of different phenomena that take place simultaneously as an industry ages but, at the same time, we recognize that it may also make the specific features of each dimension of the ILC more blurred. Furthermore, as discussed in Sections 2 and 3.2, previous works have generally taken just one dimension of an industry's evolution into account to define the stages ILC. To test the robustness of the main results with respect to each single component of the $ILC_{m,t}$ indicator, Table 10 shows the results of the preferred specification (i.e., last column of Table 6) when firms are assigned to the top 25%, middle 50% and bottom 25% values of the distributions of each component of $ILC_{m,t}$ (i.e., predominance of product over process innovation; the extent of market fragmentation; the number of product varieties; the average degree of vertical integration in the industry). Thus, the use of the composite $ILC_{m,t}$ indicator is substituted with the use of each stand-alone component.

[INSERT TABLE 10 ABOUT HERE]

On the one hand, the result regarding the higher relevance of productivity for firm survival in the "mature" stage with respect to the "early" stage of the ILC is generally confirmed for each single component of the $ILC_{m,t}$ indicator, except (partially) for $VINT_{m,t}$, the average degree of vertical integration in the industry. Given that the most vertically integrated firms are assigned to the top 25% of the $VINT_{m,t}$ distribution, the result points to the higher relevance of productivity for firm survival for the most vertically integrated firms with respect to their more dis-integrated counterparts. This result may be partly explained by Helfat (2015) that argues that in order to be integrated in the production of critical (and cost-enhancing) components during the mature stage of an industry it is essential to be very productive.

On the other hand, the higher relevance of age for firm survival in the "early" stage of the ILC is strongly confirmed when considering $FRAG_{m,t}$ (the extent of market fragmentation) $PVAR_{m,t}$ (number of product varieties introduced in the industry) and partially confirmed also when adopting $VINT_{i,\tau}$ (the average degree of vertical integration in the industry) even if the coefficients are not statistically significant. Conversely, is not confirmed when adopting $TINNOV_{m,t}$ (predominance of product over process innovation). Given that those firms more prone to process innovations are assigned to the bottom 25% of the $TINNOV_{m,t}$ distribution, the result suggests that the oldest firms may be advantaged with respect to their younger counterparts especially in the case in which process innovations are introduced in the market. This is in line with the results by Huergo and Jaumandreu (2004) in their study of the probability of introducing process innovations as a function of firm age.

Overall, the performed robustness checks confirm the main results contained in Table 6 and reassure us about the reliability of our analysis. In next section, we briefly discuss the main conclusions of the paper.

6. Concluding remarks

Despite the extended empirical literature on the determinants of firm survival and the well-established body of research on the ageing path followed by industries, little is known about how the characteristics of surviving firms evolve across different stages of the ILC (Peltoniemi, 2011, p. 366). This paper analyzes the role played by age and productivity in firm survival across three phases of an industry's evolution, by taking advantage of a representative sample of Spanish firms with ten or more employees in forty-seven 3-digit manufacturing sectors over the period 1993-2009.

Once a large set of firm characteristics, industry unobserved heterogeneity and the economic cycle have all been controlled for, two main results emerge. First, the risk of firm death differs across the stages of the ILC, being higher in the "early" phase and lower in the "intermediate" and "mature" stages. Second, the role of firm age and productivity is different across the stages. In the "early" stage of the ILC, firm age is negatively correlated with hazard rates (pointing out the role of "learning processes" and accumulation of experience in this phase), while firm productivity is not. Firm productivity is associated with lower hazard in the "mature" stage of the ILC, when competition is primarily efficiency-driven, while firm age does not play a significant role for firm survival. In the "intermediate" stage both age and productivity play a role in reducing firms' hazard rates.

The first novelty provided by this work is methodological and it makes the paper an interesting complement to the vast body of works on the ILC; the latter have usually focused on just one dimension of the "evolutionary" process industries go through, mainly captured by the time series of net entry rates, in order to define the bounds of the succeeding stages of an industry's life cycle (see, Gort and Klepper, 1982; Klepper and Graddy 1990, among others). By taking a different approach and exploiting the available information on four (and not just one) dimensions of an industry's ageing path (i.e. the dominant type of innovative activity conducted in each stage, the number of competitors and of product varieties within each stage and the evolution of the average vertical structure of the firms belonging to the industry), three stages of the ILC are defined by means of a composite indicator.

A second contribution of the paper is that it helps to qualify the role of age and productivity in firm survival: the advantage granted to more experienced and/or productive firms has been found to be specific to the competitive stage in which a firm is active. This result is consistent with the broader literature in innovation studies which formalizes the existence of unlike competitive regimes in which firms "leverage" different strategies to survive in the market. Early phases of the ILC correspond to an "entrepreneurial regime" (as defined by Winter, 1984; Audretsch, 1991; among others) in which many young entrants compete in terms of the introduction of new product varieties (product innovation) and adopt "trial and error" strategies. In this regime learning processes are fundamental to survive. As an industry ages the competitive setting changes and moves to a "routinized regime": this corresponds to the mature stage of the ILC (Audretsch and Feldman, 1996, p.256). In this setting, the innovation activity is related to knowledge that mainly involves the optimization of production processes (process innovation); no major product innovations occur (Klepper, 1997); productivity and the ability to reach an efficient scale of production become fundamental strategies to survive.

Tentatively, this work may furnish some suggestions both for managers and policy makers. Managers may benefit from knowing which stage of an industry's evolution their firms are actually facing. For example, if a firm belongs to an industry in its "early" stage, learning processes ("trial and error" strategies in the adoption of new technologies) together with investments in R&D activities (a higher percentage of workers employed in R&D activities) have been found to be relevant for survival. Conversely, for firms active in industries passing through their "mature" stage, it would be key to reach an efficient scale and enhance productivity.

Policy interventions may take into account the life-cycle stage of specific industries and the country's balance of activities in terms of industries in their "early" or "mature" stages, as suggested by Bos et al. (2013, p.89). Experimentation may be promoted in industries at an "early" stage of evolution, for example via the elimination of barriers to entrepreneurship and the promotion of product developers. Indeed, barriers to entry have been shown to be harmful for aggregate growth, especially in an advanced economy (see, Arnold, et al. 2011, p. 101, among others). Moreover, young and risk-loving entrepreneurs, as suggested by Barba Navaretti et al. (2014), are those who will most likely introduce new products and services in the market. Finally, even if our work does not provide direct evidence on this, in order to facilitate new firms' formation and successful experimentation it may be relevant to ensure a proper mechanisms of access to credit not biased against new businesses (European Commission, 2014). In "mature" industries, policies may be aimed at improving the efficiency of the bunch of existing firms that should be incentivized to pursue a more efficient allocation of resources and a larger scale. Among the possible suggestions, policy makers may pay attention to firms' restructuring processes. It would be important, for example, to promote a re-organization of firms in mature industries away from non-key phases of the production processes through, for example, sub-contracting strategies and shifts of their activities toward the "upper" links of their value chains.

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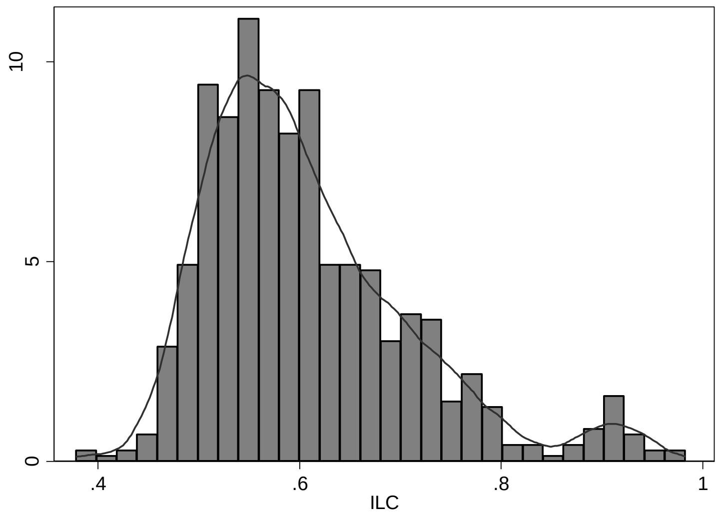
Tables and Figures

Table 1 - Values of the $ILC_{m,t}$ indicator at different percentiles of its distribution

	1%	5%	10%	25%	50%	75%	90%	95%	99%
	0.455	0.481	0.503	0.532	0.585	0.662	0.745	0.802	0.928
Min					0.378				
Max					0.983				
Mean					0.608				
Standard deviation					0.104				
Average value of the $ILC_{m,t}$ indicator by group of industries									
High-tech industries					0.614				
Low-tech industries					0.572				
No. of observations (industry/year)					732				

Notes: observations refer to forty-seven 3-digit manufacturing industries tracked over the 1993-2009 period; unbalanced panel.
For the list of the industries considered in the analysis and the adopted taxonomy in terms of technological intensity, the reader is cross-referred to Table A.3.

Figure 1 – Histogram and empirical density of the $ILC_{m,t}$ indicator



Notes: observations refer to forty-seven 3-digit manufacturing industries tracked over the 1993-2009 period; unbalanced panel.
For the list of the industries considered in the analysis the reader is cross-referred to Table A.3.

Table 2- Transition matrix across the stages of the ILC

Year t-1	*Year t* "Early" stage	"Intermediate" stage	"Mature" stage	Total	No. of observations
"Early" stage	90.91%	9.09%	0.00%	100.00%	165
"Intermediate" stage	4.08%	88.05%	7.87%	100.00%	343
"Mature" stage	0.00%	14.12%	85.88%	100.00%	177
Total	23.94%	49.93%	26.13%	100.00%	685

Notes: observations refer to forty-seven 3-digit manufacturing industries tracked over the 1993-2009 period; unbalanced panel.
Each cell contains transitions from t-1 to t: therefore, the first observation for each industry is lost.

Table 3- Firms in "de-mature" industries *versus* firms in the rest of industries

	Firms in "de-mature" industries (backward transitions)	Firms in the rest of industries (forward transitions and persistence within the same stage)
Average import share (Imports/sales, %)	8.70	8.05
No. of observations (firm/year)	*840*	*23,526*
Average extent of demand customization (1=high; 0=low)	0.587	0.595
No. of observations (firm/year)	*837*	*23,542*
Average extent of uncertainty in the final market	3.42	3.39
No. of observations (firm/year)	*566*	*14,450*

Table 4 – Firm-level descriptive statistics by stage of the ILC
Notes: standard deviations are reported in parentheses.

		Stages of the industry life cycle			
Firm-level characteristics	Measure	"Early"	"Intermediate"	"Mature"	All stages
Age = no. of years since firm establishment	Median value	19 (18.71)	21 (20.82)	24 (23.72)	21 (21.16)
Real labor productivity = gross value added at constant (1990) prices / total employees	Average value	32,610 (36,553)	51,266 (50,190)	66,262 (77,223)	49,970 (56,281)
EBITDA margin = EBITDA / sales	Average value	5.63 (26.7)	8.47 (21.24)	9.40 (16.70)	7.95 (21.91)
R&D intensity = R&D employees / total employees	Percentage	1.42% (4.27)	1.53% (4.19)	1.33% (3.79)	1.46% (4.12)
Size = total employees	Median value	29 (404.7)	49 (435.4)	56 (621.8)	42 (480.7)
Multi-plant firm (dummy variable = 1 if firm owns more than 1 plant)	Share of firms	8.55% (0.27)	14.86% (0.36)	18.40% (0.39)	14.06% (0.35)
Foreign capital (dummy variable =1 if part of the firm equity is owned by a foreign investor)	Share of firms	9.77% (0.29)	21.23% (0.41)	18.93% (0.39)	17.72% (0.38)

Table 5 - Econometric results: pooling the observations of the three stages of the ILC

Dependent variable: hazard rates	1	2	3	4	5
Stages of the ILC					
STAGE$_{INTERMEDIATE}$		0.419 ***	0.423 ***	0.507 ***	0.670 *
STAGE$_{MATURE}$		0.338 ***	0.350 ***	0.444 ***	0.601 **
Main regressors					
AGE$_2$			0.672 ***	0.688 ***	0.679 ***
AGE$_3$			0.577 ***	0.636 ***	0.739 **
PRODUCTIVITY$_M$				0.552 ***	0.776 **
PRODUCTIVITY$_H$				0.414 ***	0.480 ***
Control variables					
EBITDAM$_M$					0.313 ***
EBITDAM$_H$					0.358 ***
R&D$_M$					0.398 ***
R&D$_H$					0.732 *
SIZE$_S$					1.286
GROWTH					0.254 ***
MULTIPLANT					0.739
FOREIGN OWNERSHIP					1.154
2-digit industry dummies					
Manufacture of textiles, apparel, leather and related products					2.320 ***
Manufacture of wood and paper products, and printing					1.951 ***
Manufacture of rubber and plastic, chemicals and pharmaceutical products					1.389
Other non-metallic mineral products and metal products					1.641 **
Manufacture of computer, electronic and optical products, electrical, mach. and equipment					1.780
Manufacture of motor vehicles and other transport equipment					1.792 **
Manufacture of furniture and other manufacturing products					1.317
Year dummies					
Year 1993	0.025 ***	0.045 ***	0.059 ***	0.068 ***	(dropped)
Year 1994	0.026 ***	0.046 ***	0.062 ***	0.074 ***	0.057 ***
Year 1995	0.016 ***	0.028 ***	0.039 ***	0.052 ***	0.036 ***
Year 1996	0.016 ***	0.028 ***	0.038 ***	0.05 ***	0.045 ***
Year 1997	0.009 ***	0.016 ***	0.021 ***	0.028 ***	0.026 ***
Year 1998	0.021 ***	0.037 ***	0.052 ***	0.068 ***	0.051 ***
Year 1999	0.019 ***	0.033 ***	0.046 ***	0.060 ***	0.056 ***
Year 2000	0.001 ***	0.002 ***	0.003 ***	0.004 ***	0.004 ***
Year 2001	0.009 ***	0.017 ***	0.024 ***	0.032 ***	0.022 ***
Year 2002	0.026 ***	0.048 ***	0.068 ***	0.089 ***	0.062 ***
Year 2003	0.002 ***	0.003 ***	0.005 ***	0.006 ***	0.004 ***
Year 2004	0.010 ***	0.019 ***	0.028 ***	0.037 ***	0.027 ***
Year 2005	0.014 ***	0.027 ***	0.040 ***	0.051 ***	0.049 ***
Year 2006	0.010 ***	0.019 ***	0.028 ***	0.037 ***	0.031 ***
Year 2007	0.028 ***	0.053 ***	0.081 ***	0.104 ***	0.075 ***
Year 2008	0.048 ***	0.091 ***	0.143 ***	0.181 ***	0.111 ***
Year 2009	0.032 ***	0.063 ***	0.098 ***	0.124 ***	0.068 ***
Observations (firm/year)	24,529	24,529	24,529	24,490	20,499
Log-likelihood	-2.210	-2.162	-2.151	-2.094	-1.684

Notes: the omitted industry dummy refers to *manufacture of food and beverages*.
Significance at *10%, **5%, ***1%.

Table 6 - Econometric results: separate regressions for the three stages of the ILC

Dependent variables: hazard rates	1			2			3		
	"Early" stage	"Intermediate" stage	"Mature" stage	"Early" stage	Intermediate" stage	"Mature" stage	"Early" stage	"Intermediate" stage	"Mature" stage
Main regressors									
AGE_2	0.647 **	0.621 **	0.990	0.663 **	0.626 **	1.086	0.654 **	0.643 *	1.090
AGE_3	0.601 ***	0.549 ***	0.635	0.634 ***	0.608 **	0.791	0.753	0.751	1.048
$PRODUCTIVITY_M$				0.625 ***	0.459 ***	0.478 **	0.899	0.703 *	0.508 **
$PRODUCTIVITY_H$				0.662	0.299 ***	0.351 ***	0.588	0.399 ***	0.419 **
Control variables									
$EBITDAM_M$							0.381 ***	0.261 ***	0.320 ***
$EBITDAM_H$							0.433 ***	0.329 ***	0.323 ***
$R\&D_M$							0.237 ***	0.537	0.290
$R\&D_H$							0.838	0.643	0.529
$SIZE_S$							1.542 *	1.080	1.143
GROWTH							0.359 ***	0.203 ***	0.055 ***
MULTIPLANT							0.749	0.790	0.678
FOREIGN OWNERSHIP							1.743 *	0.773	1.577
2-digit industry dummies	No	No	No	No	No	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (firm/year)	6,363	11,049	5,797	6,353	11,030	5,787	5,324	9,141	4,779
Log-likelihood	-887.2	-886.4	-356.3	-868.7	-852.2	-347.6	-709.1	-678.6	-252

Notes: year and 2-digit industry dummies estimates omitted to save space. Complete table available from authors upon request

Significance at *10%, **5%, ***1%

Table 7 - Interaction effects of firm age and productivity on firm survival in terms of hazard ratios

	"Early" stage		"Intermediate" stage		"Mature" stage	
	AGE_2	AGE_3	AGE_2	AGE_3	AGE_2	AGE_3
$PRODUCTIVITY_M$	0.588	0.677	0.452	0.528	0.554	0.532
$PRODUCTIVITY_H$	0.385	0.443	0.257	0.300	0.457	0.439

Notes: Hazard ratios are calculated as products of pairs of coefficients that have been taken from column 3 in Table 6.
The baseline (omitted categories) is $AGE_1 * PRODUCTIVITY_L$.

Table 8 – Robustness check (I): separate regressions; the stages of the ILC are defined as the bottom, middle and top terciles (33%) of the $ILC_{m,t}$ indicator

Dependent variables: hazard rates									
	1			2			3		
	"Early" stage	"Intermediate" stage	"Mature" stage	"Early" stage	"Intermediate" stage	"Mature" stage	"Early" stage	"Intermediate" stage	"Mature" stage
Main regressors									
AGE$_2$	0.631 ***	0.534 ***	1.260	0.636 **	0.558 **	1.375	0.621 **	0.520 **	1.566
AGE$_3$	0.571 ***	0.533 ***	0.752	0.614 ***	0.598 **	0.930	0.720 *	0.670	1.367
PRODUCTIVITY$_M$				0.528 ***	0.487 ***	0.478 ***	0.834	0.757	0.509 **
PRODUCTIVITY$_H$				0.552 ***	0.277 ***	0.350 ***	0.654	0.393 ***	0.374 ***
Control variables									
EBITDAM$_M$							0.372 ***	0.227 ***	0.332 ***
EBITDAM$_H$							0.399 ***	0.385 ***	0.298 ***
R&D$_M$							0.225 ***	0.636	0.317 **
R&D$_H$							0.839	0.566	0.719
SIZE$_S$							1.496 *	0.816	1.517
GROWTH							0.342 ***	0.232 ***	0.058 ***
MULTIPLANT							0.714	1.023	0.481
FOREIGN OWNERSHIP							1.737 *	0.558 *	1.714
2-digit industry dummies	No	No	No	No	No	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (firm/year)	8,045	7,804	7,811	8,032	7,791	7,798	6,716	6,505	6,502
Log-likelihood	-1030	-655.4	-452.4	-1001	-630.3	-441.9	-817.2	-495.7	-321.4

Notes: year and 2-digit industry dummies estimates omitted to save space. Complete table available from authors upon request.
Significance at *10%, **5%, ***1%.

Table 9 - Robustness check (II): separate regressions; firm age and firm productivity enter as continuous variables in the empirical model

Dependent variables: hazard rates	1			2			3		
	"Early" stage	"Intermediate" stage	"Mature" stage	"Early" stage	"Intermediate" stage	"Mature" stage	"Early" stage	"Intermediate" stage	"Mature" stage
Main regressors									
ln AGE	0.785 ***	0.795 **	0.854	0.804 ***	0.856	1.039	0.847	0.953	1.221
ln PRODUCTIVITY				0.746 ***	0.598 ***	0.624 ***	0.867	0.706 **	0.624 ***
Control variables									
EBITDAMM							0.383 ***	0.255 ***	0.342 ***
EBITDAMH							0.451 ***	0.321 ***	0.345 **
R&DM							0.252 **	0.553 *	0.281 *
R&DH							0.820	0.624 *	0.531
$SIZE_S$							1.401	1.121	1.083
GROWTH							0.370 ***	0.204 ***	0.047 ***
MULTIPLANT							0.788	0.785	0.708
FOREIGN OWNERSHIP							1.676	0.776	1.345
2-digit industry dummies	No	No	No	No	No	No	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (firm/year)	6,363	11,049	5,797	6,319	10,963	5,726	5,293	9,086	4,726
Log-likelihood	-888.1	-888.50	-357.4	-858.2	-850.00	-335.1	-703	-678.10	-246

Notes: year and 2-digit industry dummies estimates omitted to save space. Complete table available from authors upon request.
Significance at *10%, **5%, ***1%.

Table 10 - Robustness check (III): separate regressions for each of the four components of the $ILC_{m,t}$ indicator

Dependent variables: hazard rates	Top 25% (corresponds to the "early" stage)				Middle 50% (corresponds to the "intermediate" stage)				Bottom 25% (corresponds to the "mature" stage)			
	$TINNOV_{m,t}$	$FRAG_{m,t}$	$PVAR_{m,t}$	$VINT_{m,t}$	$TINNOV_{m,t}$	$FRAG_{m,t}$	$PVAR_{m,t}$	$VINT_{m,t}$	$TINNOV_{m,t}$	$FRAG_{m,t}$	$PVAR_{m,t}$	$VINT_{m,t}$
Main regressors												
AGE_2	0.790	0.644 **	0.568 ***	0.912	0.799	0.651 *	0.709	0.607 **	0.523 **	1.161	1.026	0.800
AGE_3	0.889	0.747	0.632 **	0.841	0.938	0.686	0.815	0.673 **	0.475 **	1.223	1.218	0.886
$PRODUCTIVITY_M$	0.733	0.820	0.988	0.746	0.763	0.840	0.652 **	0.790	0.776	0.511 **	0.741	0.684 *
$PRODUCTIVITY_H$	0.548 *	0.420 **	0.589	0.297 ***	0.487 ***	0.450 ***	0.544 **	0.484 **	0.289 ***	0.402 ***	0.282 ***	0.535 *
Control variables												
$EBITDAM_M$	0.299 ***	0.325 ***	0.377 ***	0.214 ***	0.323 ***	0.296 ***	0.274 ***	0.354 ***	0.321 ***	0.285 ***	0.299 ***	0.337 ***
$EBITDAM_H$	0.483 ***	0.367 ***	0.410 ***	0.410 *	0.317 ***	0.352 ***	0.299 ***	0.414 ***	0.300 ***	0.382 ***	0.488	0.290 ***
$R\&D_M$	0.318 **	0.201 **	0.230 ***	0.481	0.424 **	0.560 *	0.480 **	0.492 *	0.489	0.331 **	0.394	0.201 ***
$R\&D_H$	0.953	1.052	0.910	0.976	0.533 **	0.581 *	0.709	0.683	0.793	0.672	0.245 ***	0.796
$SIZE_S$	1.045	1.742 **	1.510 *	0.429 **	2.348 ***	0.769	1.240	1.923 ***	0.614	2.381 **	0.959	2.000 *
GROWTH	0.324 ***	0.288 ***	0.362 ***	0.183 ***	0.217 ***	0.201 ***	0.222 ***	0.264 ***	0.154 ***	0.227 ***	0.067 ***	0.290 ***
MULTIPLANT	0.797	0.755	0.824	0.589	0.697	0.738	0.844	0.770	0.850	0.778	0.496	0.946
FOREIGN OWNERSHIP	1.071	2.578 ***	2.171 ***	0.637	1.881 **	0.607	0.782	1.121	0.272 *	1.629	1.070	2.026 **
2-digit industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (firm/year)	4,851	4,694	4,851	4,566	9,348	9,563	9,088	9,638	4,792	5,026	5,158	4,940
Log-likelihood	-572.7	-623.1	-636	-278.4	-717.8	-669.8	-739	-830	-348.2	-344.7	-257.5	-536.6

Notes: year and 2-digit industry dummies estimates omitted to save space. Complete table available from authors upon request.

Significance at *10%, **5%, ***1%.

Variable labels: $TINNOV_{m,t}$: predominance of product over process innovation; $FRAG_{m,t}$: extent of market fragmentation; $PVAR_{m,t}$: number of product varieties; $VINT_{m,t}$: average degree of vertical integration in the industry. See Section 3.2 for further details on how each variable has been built.

Appendix A

A.1. Control variables

The following vector of control variables has been included in the empirical analysis.

A measure of *firm size,* 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 the distance of the firm from the minimum efficient scale (MES). Reducing the gap from the MES is key to eliminate cost disadvantages and survive in the market (see, among others, Evans, 1987; Mata and Portugal, 1994; Audretsch and Mahmood, 1995; Coad et al. 2013). Two groups of firms and the corresponding dummy variables are defined: those from 10 to 50 employees, $\mathrm{SIZE_S}$, and those with more than 50 employees, $\mathrm{SIZE_L}$, and only the first dummy has been included in model to avoid multicollinearity.

A measure of *firm growth*, calculated as the 1-year percentage variation in the number of firm employees. Firm growth may be a key element for firm survival, especially for those firms which have not reached the MES yet: indeed, as suggested by Lotti et al. (2009), market selection operates with the correlated exit of the less efficient firms and the convergence to the MES of the most efficient ones.

A measure of *firm profitability*, calculated as the EBITDA margin (EBITDA/sales) at the end of the year. It is reasonable to expect that firm survival chances will be affected by the ability of firms to generate stable flows of earnings in the medium/long run 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, three dummy variables have been built, respectively indicating low profitable firms (those which show a value lower than the 25^{th} percentile), $\mathrm{EBITDAM_L}$, medium profitable firms (values between the 25^{th} and the 75^{th} percentile), $EBITDAM_M$, and high profitable firms (values higher than the 75^{th} percentile), $EBITDAM_H$. Two out of three dummies have been introduced to avoid multicollinearity.

A measure of *R&D intensity*, calculated as the ratio of the number of employees in R&D activities to the total number of employees at the end of the year. Firms are able to affect their survival probability through R&D activities, which lead to new product development, quality improvement in existing products and services and reductions in the costs of production (see Kim and Lee, 2011, among others). After having calculated the median value of the ratio for the entire sample, three groups of firms are defined: those firms with zero R&D employees, $\mathrm{R\&D_L}$, those showing a ratio below the median value, $R\&D_M$, and those showing a ratio above the median value, $R\&D_H$. Two out of three dummies have been introduced to avoid multicollinearity.

A year dummy variable that takes value equal to 1 for multi-plant firms, $\mathrm{MULTIPLANT}$, and taking value 0 otherwise. In adverse conditions, multi-plant firms can bear the failure of one of their plants without exiting the market, while single-plant cannot (Mata and Portugal, 1994).

A yearly dummy variable taking value equal to 1 for those firms which are (partially or entirely) owned by foreign investors, $\mathrm{FOREIGN}$, and taking value 0 otherwise. Foreign participation may foster access to external technology, which could improve firm efficiency and its survival chances. Yet, the empirical evidence is not conclusive (Görg and Strobl, 2003; and Mata and Portugal, 2002, 2004).

A vector of 2-digit industry dummies has been included in the empirical model to control for time-invariant sectoral specific unobserved heterogeneity. Finally, a vector of year dummies (1993-2009) has been introduced to capture the role of the business cycle.

All control variables enter the empirical model as 1-year lagged to reduce potential simultaneity problems. Table A.2 shows the Pearson correlation coefficients between all pairs of independent variables included in the empirical analysis.

Table A.1- Correlation matrix for the four components of the $ILC_{m,t}$ indicator

	TINNOV	*FRAG*	*PVAR*	*VINT*
TINNOV	*1*			
FRAG	*0.1788**	*1*		
PVAR	*0.5069**	*0.2493**	*1*	
VINT	*-0.1275**	*-0.4199**	*-0.3441**	*1*

Notes: the correlation coefficient having an asterisk means that it is statistically significant at 5% (or lower).

Table A.2 – Correlation matrix for the independent variables

	AGE_2	AGE_3	$PRODUCTIVITY_M$	$PRODUCTIVITY_H$	$EBITDAM_M$	$EBITDAM_H$	$R\&D_M$	$R\&D_H$	$SIZE_S$	GROWTH	MULTIPLANT	FOREIGN OWNERSHIP
AGE_2	1											
AGE_3	-0.6706	1										
$PRODUCTIVITY_M$	0.0248	-0.0496	1									
$PRODUCTIVITY_H$	-0.1008	0.1775	-0.5739	1								
$EBITDAM_M$	-0.0423	0.0718	0.0657	0.1572	1							
$EBITDAM_H$	0.1306	-0.2092	0.0814	-0.2384	-0.5758	1						
$R\&D_M$	-0.1180	0.2006	-0.0072	0.1543	0.0714	-0.2394	1					
$R\&D_H$	-0.0798	0.1147	-0.0066	0.1301	0.0771	-0.1182	-0.1695	1				
$SIZE_S$	0.2145	-0.3525	0.0618	-0.3373	-0.2438	0.5115	-0.4317	-0.1586	1			
GROWTH	-0.0030	-0.0383	0.0051	-0.0225	0.0767	-0.0363	0.0374	-0.0067	-0.0647	1		
MULTIPLANT	-0.1181	0.1798	-0.0656	0.1917	-0.0232	-0.1889	0.2244	0.0320	-0.3335	0.0406	1	
FOREIGN OWNERSHIP	-0.1317	0.1926	-0.0832	0.3058	0.0670	-0.2549	0.2915	0.0780	-0.4431	0.0286	0.2317	1

Table A.3 – List of the forty-seven 3-digit (NACE rev.2 classification) manufacturing industries for which the $ILC_{m,t}$ indicator has been calculated

NACE code	Description of the industry
10.1	Processing and preserving of meat and production of meat products
10.2	Processing and preserving of fish, crustaceans and molluscs
10.3	Processing and preserving of fruit and vegetables
10.5	Manufacture of dairy products
10.7	Manufacture of bakery and farinaceous products
10.8	Manufacture of other food products
11.0	Manufacture of beverages
13.2	Weaving of textiles
13.9	Manufacture of other textiles
14.1	Manufacture of wearing apparel, except fur apparel
15.1	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery and harness; dressing and dyeing of fur
15.2	Manufacture of footwear
16.2	Manufacture of products of wood, cork, straw and plaiting materials
17.1	Manufacture of pulp, paper and paperboard
17.2	Manufacture of articles of paper and paperboard
18.1	Printing and service activities related to printing
20.1	Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms
20.3	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
20.4	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
21.1	Manufacture of basic pharmaceutical products
21.2	Manufacture of pharmaceutical preparations
22.1	Manufacture of rubber products
22.2	Manufacture of plastic products
23.1	Manufacture of glass and glass products
23.3	Manufacture of clay building materials
23.4	Manufacture of other porcelain and ceramic products
23.6	Manufacture of articles of concrete, cement and plaster
23.7	Cutting, shaping and finishing of stone
24.1	Manufacture of basic iron and steel and of ferro-alloys
24.4	Manufacture of basic precious and other non-ferrous metals
25.1	Manufacture of structural metal products
25.2	Manufacture of tanks, reservoirs and containers of metal
25.5	Forging, pressing, stamping and roll-forming of metal; powder metallurgy
25.6	Treatment and coating of metals; machining
25.7	Manufacture of cutlery, tools and general hardware
25.9	Manufacture of other fabricated metal products
26.1	Manufacture of electronic components and boards
27.1	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus
27.4	Manufacture of electric lighting equipment
28.1	Manufacture of general-purpose machinery
28.2	Manufacture of other general-purpose machinery
28.9	Manufacture of other special-purpose machinery
29.2	Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers
29.3	Manufacture of parts and accessories for motor vehicles
30.1	Building of ships and boats
31.0	Manufacture of furniture
32.1	Manufacture of jewellery, bijouterie and related articles

Notes: in Section3.2, industries have been grouped into "high-tech" and "low-tech" in order to check the correspondence of the stages identified by the $\boldsymbol{ILC_{m,t}}$ indicator with the level of technological intensity of the industry. The taxonomy followed is a more aggregated version of that provided by Eurostat (see the web-page http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:High-tech_classification_of_manufacturing_industries). High-tech industries are highlighted in grey.