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Innovation and business survival: A long-term approach

José M. Ortiz-Villajos[a,*], Sonia Sotoca[b]

[a] Complutense University of Madrid, Faculty of Economics, Department of Applied and Structural Economics & History, Campus de Somosaguas, 28223-Pozuelo de Alarcón, Madrid, Spain

[b] Complutense University of Madrid, Faculty of Economics, Department of Economic Analysis & Quantitative Economics, Campus de Somosaguas, 28223-Pozuelo de Alarcón, Madrid, Spain

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ABSTRACT

This paper explores the influence of innovation on the probability of survival of two hundred top British firms founded throughout the nineteenth and twentieth centuries. To this end, we have collected the firms' significant innovations and classified them by Schumpeterian types, patented and non-patented and domestic and imported. The number of patents registered by the firms throughout their lifetime −a rough measure of their incremental innovation activity– has also been recorded. In addition, twelve control variables −five characteristics of the firms and seven of their business leaders– have been included. Both log-normal and gamma duration models have been used in the analysis. They have been estimated, firstly for the whole set of firms and, secondly, for the manufacturing and the service firms separately to control for industry differences. The results of the log-normal and gamma estimations are highly coincident, with some nuances. The significant innovations −particularly new processes, non-patented and domestic ones– have been found to positively influence the probability of business survival. The number of patent applications seems to increase the survival probability of the manufacturing firms, but not of the service ones. Among the control variables, the firm's size, its international dimension, and the age of the business leader at entry seem to be the most influential ones on business survival, although there are some differences between manufacturing and services. The main results are robust to the division of the sample by entry period.

1. Introduction

Most firms aspire to last for long, but only some of them manage to survive more than a few years. Thus, durability is a clear indicator of business success, the key one according to Barnard (1938). Not surprisingly, business survival has attracted the interest of many scholars since a long time ago. Among the variety of factors considered to influence business longevity,[1] innovation is a prominent one. Many studies analyzing the relationship between both variables have been published, but the theme is far from exhausted as some conflicting results have appeared and many aspects of that relationship remain unexplored. This is in part due to the difficulty to obtain data on innovation, especially in disaggregated terms. In addition, data are usually available only for short periods of time, hindering long-term analyses, particularly valuable when studying longevity.

The present paper aims to delve in the two aforementioned directions. To this end, we have constructed an ad hoc data set of innovations introduced by the arguably top two hundred British companies of the nineteenth and twentieth centuries. Therefore, the study does not deal with average firms, but with a selected group of outstanding ones. They were outstanding in several aspects, including durability, compared with the average firm, but at the same time they were very diverse, also in terms of longevity. Our purpose is to study the factors influencing that survival diversity. In particular, we will test whether the selected firms' longevity was related with their innovation activity (level and type), controlling for some features of the companies and of their founders/leaders.

The rest of the paper is organized as follows. Section 2 contains an overview of the previous literature, including an explanation of our motivations and contributions. In Section 3, the sources, data and approach of the study are described. The explanatory and control variables and the empirical duration models used are explained in Section 4. The results of the estimations of the econometric models and a robustness check are presented in Section 5. Section 6 concludes.

2. Related literature and research motivation

Business survival has been found to be influenced by many factors,

* Corresponding author.
E-mail addresses: jmortizv@ccee.ucm.es (J.M. Ortiz-Villajos), sotoca@ccee.ucm.es (S. Sotoca).

[1] The terms 'survival', 'longevity' or 'durability' will be used indistinctly throughout the paper.

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such as the characteristics of the market (Audretsch and Mahmood, 1995; Mata et al., 1995; Agarwal and Gort, 2002), the industry life cycle (Agarwal, 1997), the sector's technological intensity (Schumpeter, 1942; Audretsch, 1995; Mata et al., 1995; Aghion et al., 2001), the size and age of the firm (Evans, 1987; Geroski, 1995; Sutton, 1997; Cefis and Marsili, 2005), its profitability and financial constraints (Headd, 2003; Bellone et al., 2008), its innovation activity (Hall, 1987; Ericson and Pakes, 1995; Esteve-Pérez et al., 2004; Cefis and Marsili, 2005), its pre-entry experience (Boeker, 1988; Klepper, 2002; Thomson, 2005), as well as the founder's personal features (Vivarelli and Audretsch, 1998; Arrighetti and Vivarelli, 1999; Headd, 2003; Persson, 2004; Colombo and Grilli, 2005; Arribas and Vila, 2007; Saridakis et al., 2008).[2] Factors like size, age or profitability of the firm have received prominent attention by empirical studies on survival, but the interest in innovation has increased recently.

Several studies have shown a positive influence of innovation on survival, although others have not found a clear relation or have detected conflicting effects (Jensen et al., 2008; Buddelmeyer et al., 2010; Børing, 2015). This is partially explained by the variety −in nature and quality– of the innovation measures used, which also makes comparisons across studies difficult (Buddelmeyer et al., 2010, p. 265). Specialists have highlighted the necessity of fitter and more disaggregated data at the firm level to solve the conflicting results and to better understand how innovation affects survival (Cefis and Marsili, 2006; Børing, 2015).

Most studies on the relationship between innovation and business survival have used R&D and/or patent data (e.g., Geroski, 1995; Audretsch, 1995; Esteve-Pérez et al., 2004; Buddelmeyer et al., 2010; Tsvetkova et al., 2014; Ugur et al., 2016; Kim and Lee, 2016). The problems of such indicators as measures of innovation imply certain limits in the analyses based on them,[3] notwithstanding the valuable insights they have provided. Although all measures of innovation are imperfect (Neely and Hii, 1998, p. 37), innovation counts is probably the best one as it is not a proxy but a direct reflection of the innovation activity (Geroski, 1994, pp. 7–12; Neely and Hii, 1998, p. 36). But these indicators are particularly scarce, a reason why business survival studies using them are less abundant. Nevertheless a growing number of them have appeared in the last years (Cefis and Marsili, 2005, 2006, 2011, 2012; Klepper and Simons, 2005; Fontana and Nesta, 2009; Børing, 2015; Sharif and Huang, 2012).[4]

The latter studies have obtained the data on innovation outputs from Community Innovation Surveys (CIS) (Cefis and Marsili, 2005, 2006, 2011, 2012; Børing, 2015), specialized journals and company reports (Klepper and Simons, 2005; Fontana and Nesta, 2009) or ad hoc company surveys (Sharif and Huang, 2012). Like them, the present one analyzes the influence of innovation outputs on business survival at the firm level, but unlike them (except Klepper and Simons, 2005) it adopts a long-term approach, so the sources used by the mentioned studies −covering a short time span– are not useful for our purposes. In order to get the kind of data we need, we have resorted to the prosopographical method, that is, to a systematic collection of information from business biographies, which will be described in Section 3.

An important contribution by Cefis and Marsili (2005, 2006) was to show that the effect on survival of product and process innovations −in both cases positive ('innovation premium')– had some significant differences, indicating the interest of disaggregating innovations by types (see also Børing, 2015 and Cefis and Marsili, 2011, 2012). But, according to Schumpeter's (1934) taxonomy, in addition to product and process, there are another three kinds of innovations (organizational, new markets, and new sources of supply), of which relation with business survival has not yet been explored.[5] Thus, building upon the aforementioned contributions, the present study widens the focus to all Schumpeterian forms of innovation, aiming at testing their potentially different effect on business survival.

But innovation can be disaggregated by other criteria also useful to better understand its nature as well as its relation with longevity. This study has included two additional classifications. First, we have distinguished between patented and non-patented innovations. Due to their potential differences in nature, their effect on business survival may differ, but there is almost no evidence about this. It is true that some studies have found differential effects of patents and trademarks on survival (Buddelmeyer et al., 2010; Helmers and Rogers, 2010), showing the interest of disaggregating innovations in this way, but trademarks can only be considered a proxy of certain (marketing) innovations, not a measure of all non-patented innovations. The present study takes a step forward in this sense as it distinguishes between patented and all kinds of non-patented innovations. Secondly, we have also disaggregated the innovations between domestic and imported ones as they may also have different characteristics and a differential effect on survival. We are not aware of previous research on this, so we expect to make a contribution on the matter.

It has been debated whether the economic impact of radical innovations appearing occasionally is greater than that of incremental ones arising much more frequently. Schumpeter (1934) gave more importance to the former, while Usher (1954) emphasized the relevance of the latter, to cite two classical views. Over time, opinion has grown that the cumulative effect of incremental innovations may be the most important (Rosenberg, 1982, pp. 62–70; Fagerberg, 2005, pp. 7–8).[6] But the focus of these analyses has been the effect of the two types of innovation on productivity, few of them having tried to measure their influence on survival (Buddelmeyer et al., 2010). In order to add some evidence on this, we have recorded two different innovation indicators: (1) the significant (radical or important) innovations developed by the selected firms, and (2) the total amount of patents registered by them throughout their lifetime, which may be seen as a rough proxy of their more ordinary (incremental) innovation activity as explained in detail in subsection 4.1.

Most empirical studies on innovation and business longevity have focused on the manufacturing sector (Evans, 1987; Hall, 1987; Audretsch, 1995; Esteve-Pérez et al., 2004; Cefis and Marsili, 2005, 2006; Klepper and Simons, 2005; Fontana and Nesta, 2009; Tsvetkova et al., 2014; Kim and Lee, 2016). This is partially explained by the greater availability of data on that sector, but given the importance of the service industry in modern economies, it seems convenient to analyze it as well. In fact, researchers are increasingly looking at both manufacturing and services (Persson, 2004; Buddelmeyer et al., 2010; Helmers and Rogers, 2010; Sharif and Huang, 2012; Børing, 2015; Ugur et al., 2016), finding significant differences between them in terms of business survival. Following these contributions, our data set also includes both manufacturing and service companies.

[2] For a survey of the literature on business survival from the viewpoint of industrial organization, see Manjón-Antolín and Arauzo-Carod (2008), and Riviezzo et al. (2015) from the management and business history perspectives.

[3] Without going into detail, it can be said that the general limitation of both indicators is that, by definition, they can only reflect part of the innovation activity, so studies based only on them may undervalue the innovation activity of firms, sectors, etc. In addition, R&D is not properly an indicator of innovation but of the effort to increase the scientific and technical capabilities, which may have various orientations. Patents are neither, strictly speaking, an indicator of innovation, although they are so more properly than R&D. In any case, they are also a partial indicator as many innovations are not patented for a variety of reasons (e.g., Cohen et al., 2000). For two useful overviews on the matter, see Griliches (1990) and Geroski (1994, pp. 6–7).

[4] Studies using innovation output measures to analyze business performance indicators different from survival (Gunday et al., 2011; Baumann and Kritikos, 2016) or other aspects like persistence in innovation behavior (Tavassoli and Karlsson, 2015) have also appeared lately.

[5] The analysis of all the Schumpeterian forms of innovations has been highlighted as a lacuna of innovation studies in general (Shane, 2003, p. 34). Certainly the lacuna has begun to be filled by a number of studies (e.g., Ruef, 2002; Gunday et al., 2011; Tavassoli and Karlsson, 2015), but not in the specific case of business survival research as far as we know.

[6] Mokyr (1990, Chapter 11) differentiates between macro inventions and micro inventions (not innovations), concluding that both types are complementary and indispensable for technological progress.

The aforementioned studies have predominantly a short-term approach, analyzing the firms' hazard of exit within a span of a few years. Unlike them, our study covers a very long period, but it builds upon their findings in many aspects. On the other hand, the empirical studies on survival with a long-term approach (e.g., Carroll et al., 1996; Klepper, 2002; Thomson, 2005; Cabral and Wang, 2013) have not normally focused on innovation, but we have built on them in other aspects since their object of study – firms entering and exiting at different points in time throughout the years – is similar to ours.[7]

3. Data

3.1. Source and population of the study

As has been explained, the data for the present study −not readily available– have been collected 'by hand' from business biographies. They are a valuable source of information because out of the entrepreneurs' biographies it is possible to obtain a variety of data about them and their firms in order to analyze different aspects of their activity. In fact, this (prosopographical) method has already demonstrated its usefulness to analyze questions dealing with the wealth distribution, education, management, financing and performance of top business leaders/firms (Nicholas, 1999a,b; Tortella et al., 2009, 2013; Fellman, 2014; Toninelli and Vasta, 2014), but not with their innovation activity and survival. This is a gap of the literature which is worth filling; the present study trying to do a contribution in this line by analyzing the relation between innovation and survival of the allegedly top two hundred British business leaders/firms[8] of the nineteenth and twentieth centuries. They have been selected among those contained in the well-known *Dictionary of Business Biography* (DBB) (Jeremy and Shaw, 1984-86), which intends to include the most remarkable British entrepreneurs/firms. Although there is always room for debate, the great majority of them have been considered to have enough merits to be included in the dictionary (see Nicholas, 1999b, pp. 692-4).

The prime qualification for entry to the DBB was the "achievement of some considerable business impact […] rather than political, charitable or community work" (Jeremy, 1984, p. 5). In words of the promoters of the dictionary, the "result is neither a random nor a stratified sample, but it does, we suggest, provide a balanced and comprehensive coverage of those who have made a significant contribution to business leadership in Britain over the last 120 years" (Jeremy and Shaw, 1984-86, vol I, p. viii).[9] The elite of two hundred entrepreneurs/firms has been selected with the same criteria as the DBB, that is, according not to their size or longevity but to their "business impact" and "contribution to business leadership".[10] So, they are allegedly the most influential firms in their sectors, significantly contributing to shape them and becoming reference actors in the national and (in many cases) in the international context. Naturally, this is reflected in a performance above the average in several features (size, survival, etc.), but they are far from homogeneous in those aspects, as will be shown in Section 4.

Although this selection can be debated, the firms included (such as Austin, Baring, Barclays, Cadbury, Clark, Deloitte, Dunlop, Glaxo, Guinness, John Lewis, Marks & Spencer, Morris, Platt, Reuters, Rolls-Royce, Vickers, etc.) are generally recognized as outstanding (see Appendix A for the complete list). It is also important to point out that we have not selected them (nor has the DBB done so for the whole list) because of their innovative character, but mainly considering their great business impact. That is, the selection is not a list of the most innovative companies. To sum up, the study deals with the innovation activity and survival of an elitist group of British firms, presumably the most remarkable ones of the nineteenth and twentieth centuries. The option of focusing on a selective sample of companies instead of on a random one has its problems. For instance, the results of the study cannot be easily extrapolated to average firms, at least automatically. But we believe that analyzing outstanding companies can be very useful as there are many things to learn from them. In addition, the great influence they exert in the economy as a whole makes their analysis appealing and relevant per se as the studies cited in the following paragraph (and in the first one of the present subsection) have shown.

Our study is based on a selection of 200 top firms −and not another number– for several reasons. One of them is that some experts on the DBB have already done that selection and obtained interesting results with it (Tortella et al., 2009). But they have analyzed the relation between education (of the business leaders) and firm performance, not between innovation and business survival. Hence, we considered worth using the same selection (with some variations as explained in footnote 13) for our study. Besides, other influential academic studies on firm performance and survival have also been based on samples of 100–200 top companies,[11] so their usefulness is contrasted. This is also the case in the business and economic spheres, where rankings and reports of the top 50, 100, 200 or 500 firms are widespread.[12] Finally, the size of the sample had to be assumable for us in terms of cost given that we had to build the whole database from scratch, this being very much time consuming.[13]

3.2. Temporal and sectoral coordinates

The temporal distribution of the two hundred selected business leaders/firms follows, by and large, that of the DBB as a whole. The first entrepreneur was born in 1793 and the last one in 1918 (1789 and 1925 respectively for the DBB), while the first to die was in 1872 and the last one in 2002 (1868 and 2008 respectively for the DBB). The entry date in our analysis is the year when the entrepreneurs founded (or became leaders of) their companies,[14] the first one doing so in 1816 and the last one in 1957. The exit date is the year of the firm's liquidation,

[7] Klepper and Simons (2005) is one of the few empirical studies analyzing the relation between innovation and business survival in the long run. In this sense, it is similar to ours, but its approach is quite different, among other things because it focuses on four specific products (automobiles, tires, televisions, and penicillin) during industry shakeouts. On the other hand, business history and strategic management studies on longevity have frequently adopted a long-term approach, but they are based on case studies rather than on quantitative analysis of groups of firms. In addition, they are rarely focused on innovation, although this factor has a significant role in the narratives of some of them (e.g., Chandler, 1977, 1990; Aldrich and Auster, 1986; Sull, 1999; Fleck, 2009).

[8] A company is the making of a business leader, so the entrepreneur and the firm are somehow inseparable. It is obvious, though, that the features of the firm (size, etc.) are different from the personal traits of the entrepreneur (education, etc.), so we shall distinguish between them in the analysis. When we use the term firm, we refer to company or enterprise, not plant, throughout the whole text.

[9] The entrepreneurs were selected by a rigorous process with the advice of a group of experts. For more details, see the Introduction to the first volume of the DBB.

[10] Our selection builds upon the "Elite of 200 English entrepreneurs" established by Tortella et al. (2009), but we have modified it because our focus is the firm rather than the entrepreneur. This means that when two (or three) entrepreneurs have worked together in the same firm, we have considered them a 'unit'. So, in order to have a list of 200 leading companies, we have enlarged Tortella's selection. To sum up, our database consists of 200 firms (or business groups) and contains information of 217 entrepreneurs included in 211 biographies (18% of the DBB).

[11] For example, Chandler (1990) is based on the top 200 industrial companies of the USA, UK and Germany; Hannah (1998), on the world's largest 100 industrial corporations; Whittington and Mayer (2000), on the top 100 British, French, and German companies; and Cassis and Brautaset (2003), on the top 100 companies of several European countries.

[12] The size of those lists depends on several criteria such as the size of the sector or the country, but also on a certain discretional decision. Usually, the larger the list, the less information of each company it provides. Hence, the analytical reports on top companies are mostly based on the top 50, 100 or 200 firms (Thomson Reuters Top 100 Global Innovators; Pwc global top 100 companies, etc.).

[13] In particular, we spent a whole year to collect the information on the 200 firms.

[14] The DBB describes the history of each company from the point of view of its key business leader (the one that made the firm outstanding), whether founder or not. Hence, it provides information (on the variables included in the model) mostly on the period after that key business leader became the head of the company. This is why we have taken that year as the entry date, which coincides with the firm's foundation year when the business leader is the founder.

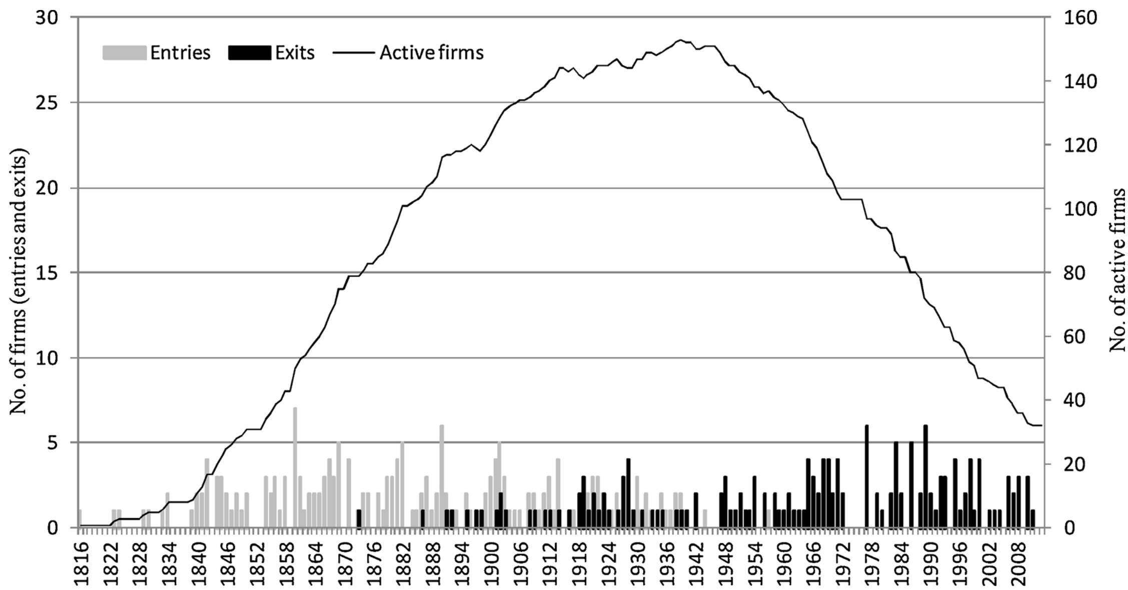

Fig. 1. Entries, exits and active firms, 1816–2013.

bankruptcy or absorption by another company[15] up to 2013, when the information was collected.[16] It is certain that not all types of exit are the same and that this could be taken into account in the analysis as some recent studies have done (e.g., Cefis and Marsili, 2011, 2012; Børing, 2015). Nevertheless, in this case we decided – as most survival studies so far– to focus on the firms' longevity and not on how they exited because the firms in our data set were born to last and not to be sold or transferred in a few years as many startups aim nowadays. Hence, the end of the original entrepreneurial project (firm), either by acquisition or death, could be considered a failure from that point of view. This does not exclude the possibility and interest of distinguishing between types of exit, but that would be the object of a different paper.

To sum up, our data set constitutes a "flow" of companies entering and exiting at different points in time from 1816 to 2013, so it is right-censored to 2013 as we do not know what happened with the surviving companies after that year. The flow of entries and exits is shown by Fig. 1, which also includes the number of active firms throughout the whole period.

Table 1 shows the distribution of the selected firms by spell duration, main industrial sector and entry period (We have distinguished between firms entering during the golden age of the British economy in terms of world dominance, c. 1815–1875, and afterwards). Their most common longevity in all has been between 51 and 100 years (46.5% of the firms), only 21% of them having survived less than 50 years. The average duration was 85.4 years.[17] This longevity is outstanding given that very few companies survive more than ten years (Shane, 2003, p. 5), although it is important to point out that the range of variation in survival time among our selected firms is enormous (from 14 to 184 years). In relation with their main sector of activity, manufacturing accounts for 70% of the firms, and services for the remaining 30%.[18] Apart from the exclusion of the agricultural sector, this is a well-known bias of the DBB considering that the weight of manufacturing in a balanced list of firms should be of about 46% according with the employment share of manufacturing in the British economy.[19] However, as we do not intend our set of companies to be a proportional representation of the whole British business sector but of the most remarkable British companies (these being notoriously more abundant in manufacturing),[20] controlling for industry differences – manufacturing versus services– within our sample is not inadequate.[21]

Table 1
Firms' distribution by spell duration to 2013, main industrial sector, and entry period.

	Firms entering in 1816–1875		Firms entering in 1876–1957		All firms	
	Number	%	Number	%	Number	%
Spell duration:						
14–50 years	9	10.7	33	28.4	42	21.0
51–100 years	31	36.9	62	53.4	93	46.5
More than 100 years	44	52.4	21	18.1	65	32.5
All firms	84	100.0	116	100.0	200	100.0
Main industrial sector:						
Manufacturing	61	72.6	79	68.1	140	70.0
Services	23	27.4	37	31.9	60	30.0
All firms	84	100.0	116	100.0	200	100.0

[15] In this we follow other studies such as Esteve-Pérez et al. (2004), for which "A firm is computed to exit in year t when this is the last year of independent operation by the firm. Therefore exit includes permanent closure, firm in liquidation, shift to [… other] activities and being acquired by another firm. When two firms merge, we […] consider the bigger one in the merger as a continuing firm and the smaller firm as an exiting one" (Ibid., p. 257).

[16] The DBB gives information previous to 1984-86, so data for subsequent years have been obtained from other sources such as the companies' web pages or the *Oxford Dictionary of National Biography*.

[17] With little variation between the manufacturing (85.8 years) and the service firms (84.4 years). The median longevity is 83.5 years for the whole set, 82.5 for the manufacturing group, and 85.5 for the services one (see Table 2).

[18] Given that there are only 4 construction firms (2%), we have included them in the services group for the analysis.

[19] Estimation made by Nicholas (1999b, p. 694) based on the sectoral shares of employment in Britain calculated by Broadberry (1998) for the period 1870–1990.

[20] The share of the manufacturing sector in the DBB as a whole is 66% (Nicholas 1999b, p. 694), almost the same as the elite's.

[21] Anyway, weighting the empirical results is not necessary when the endogenous variable is continuous, as is our case. It is certain that when the endogenous variable is binary (0–1) or multinomial, the sub-sample sizes must be fixed to the population percentage of each qualitative outcome to avoid sample selection biases. If it is impossible or inconvenient to do this, an alternative is optimizing a weighted likelihood function with different weights to the addends corresponding to the over- and under-sampled populations.

Table 2
Summary statistics.

	All firms		Manufacturing firms		Service firms		Firms entering in 1816–1875		Firms entering in 1876–1957	
	Mean (S.E.)	Median	Mean (S.E.)	Median	Mean (S.E.)	Median	Mean (S.E.)	Median	Mean (S.E.)	Median
Spell duration (Years)	85.43 (37.58)	83.50	85.86 (36.22)	82.50	84.43 (40.90)	85.50	103.63 (40.45)	106.50	72.25 (29.09)	73.00
Significant Innovations − SI (Number)	2.66 (1.71)	2.00	2.87 (1.75)	3.00	2.15 (1.53)	2.00	2.61 (1.80)	3.00	2.69 (1.65)	2.00
SI by Schumpeterian forms:										
New Product SI	1.09 (1.30)	1.00	1.30 (1.39)	1.00	0.58 (0.89)	0.00	0.90 (1.09)	1.00	1.22 (1.42)	1.00
New Process SI	0.72 (1.04)	0.00	0.78 (1.05)	0.00	0.58 (1.01)	0.00	1.02 (1.24)	1.00	0.50 (0.80)	0.00
Organizational SI	0.33 (0.67)	0.00	0.26 (0.50)	0.00	0.48 (0.95)	0.00	0.25 (0.56)	0.00	0.38 (0.74)	0.00
Marketing SI	0.36 (0.66)	0.00	0.38 (0.67)	0.00	0.30 (0.62)	0.00	0.27 (0.63)	0.00	0.41 (0.67)	0.00
New Market SI	0.07 (0.31)	0.00	0.05 (0.22)	0.00	0.12 (0.45)	0.00	0.08 (0.39)	0.00	0.06 (0.24)	0.00
New Source of Supply SI	0.06 (0.28)	0.00	0.06 (0.27)	0.00	0.05 (0.29)	0.00	0.06 (0.28)	0.00	0.06 (0.27)	0.00
Patented/Non-patented SI:										
Patented SI	1.00 (1.42)	0.00	1.26 (1.53)	1.00	0.40 (0.87)	0.00	1.01 (1.38)	0.00	0.99 (1.45)	0.00
Non-patented SI	1.66 (1.37)	1.00	1.61 (1.33)	1.00	1.75 (1.47)	2.00	1.60 (1.39)	1.00	1.70 (1.36)	2.00
Domestic/Imported SI:										
Domestic SI	2.22 (1.56)	2.00	2.36 (1.63)	2.00	1.87 (1.33)	2.00	2.20 (1.72)	2.00	2.22 (1.44)	2.00
Imported SI	0.40 (0.71)	0.00	0.46 (0.75)	0.00	0.25 (0.57)	0.00	0.39 (0.73)	0.00	0.41 (0.70)	0.00
Total patent applications (Number)	1,463.71 (8,004.84)	19.50	2,026.86 (9,510.00)	37.50	149.67 (738.97)	1.00	886.82 (6,763.99)	14.00	1,881.45 (8,800.11)	25.50
Other characteristics of the firm:										
Firm's size (No of employees)	23,886.24 (56,356.00)	5,558.00	18,455.63 (38,545.66)	5,808.00	36,557.67 (83,538.22)	5,000.00	15,723.75 (37,876.00)	4,000.00	29,797.01 (66,155.51)	8,901.00
Multinational (Yes = 1; No = 0)	0.52 (0.50)	1.00	0.47 (0.50)	0.00	0.62 (0.49)	1.00	0.39 (0.49)	0.00	0.60 (0.49)	1.00
Exports (Yes = 1; No = 0)	0.87 (0.34)	1.00	0.91 (0.29)	1.00	0.77 (0.43)	1.00	0.90 (0.30)	1.00	0.84 (0.37)	1.00
Outstanding Corporate Social Responsibility (CSR) (Yes = 1; No = 0)	0.18 (0.39)	0.00	0.21 (0.41)	0.00	0.12 (0.32)	0.00	0.20 (0.40)	0.00	0.16 (0.37)	0.00
Family business tradition (Years)	29.68 (39.06)	15.00	30.11 (36.92)	18.50	28.67 (43.95)	6.00	25.20 (33.02)	11.00	32.91 (42.75)	23.00
Business leader's personal traits:										
Age at entry (Years)	30.01 (7.68)	29.00	29.45 (7.34)	28.00	31.32 (8.32)	30.00	27.75 (5.48)	27.00	31.65 (8.59)	30.00
Founder (Yes = 1; No = 0)	0.53 (0.50)	1.00	0.51 (0.50)	1.00	0.55 (0.50)	1.00	0.57 (0.50)	1.00	0.49 (0.50)	0.00
Similar previous sector (Yes = 1; No = 0)	0.84 (0.37)	1.00	0.85 (0.36)	1.00	0.82 (0.39)	1.00	0.88 (0.33)	1.00	0.81 (0.39)	1.00
College studies (Yes = 1; No = 0)	0.26 (0.44)	0.00	0.25 (0.43)	0.00	0.28 (0.45)	0.00	0.17 (0.37)	0.00	0.33 (0.47)	0.00
Apprenticeship (Yes = 1; No = 0)	0.34 (0.47)	0.00	0.36 (0.48)	0.00	0.28 (0.45)	0.00	0.43 (0.50)	0.00	0.28 (0.45)	0.00
Inventor (Yes = 1; No = 0)	0.21 (0.40)	0.00	0.23 (0.42)	0.00	0.15 (0.36)	0.00	0.24 (0.43)	0.00	0.18 (0.39)	0.00
High social background (Yes = 1; No = 0)	0.14 (0.34)	0.00	0.11 (0.32)	0.00	0.18 (0.39)	0.00	0.08 (0.28)	0.00	0.17 (0.38)	0.00
No of observations	200		140		60		84		116	

Standard Errors (S.E.) in brackets.

4. Variables and empirical model

Given that our main objective is to analyze the relation between the innovation activity and the longevity of the two hundred selected British companies, the key explanatory variables in the study deal with innovation. In particular, we have used two different measures of the firms' innovation activity: their significant innovations and their overall patent applications. In addition, we have included twelve control variables, five related with characteristics of the firm and seven with its founder or business leader. Summary statistics for all the variables, distinguishing by groups of firms (all of them; manufacturing and services; firms entering before and after 1875) are presented in Table 2.

4.1. Explanatory variables

Several studies have used significant innovations to analyze the relation between innovation and business performance (e.g., Scherer, 1982; Pavitt, 1984; Geroski, 1994; Fontana et al., 2012). Their data sets of innovations have normally been selected by experts. The present one follows the same criterion, the 'experts' being in this case the authors of the DBB. That is, we have compiled the significant innovations developed by the two hundred selected firms as reported in the DBB. Like the SPRU database, we have recorded innovations "successfully commercialized or used in the United Kingdom, whether first developed in the UK or in any other country" (Pavitt, 1984, p. 344). But the latter includes only product and process innovations of some manufacturing sectors, while ours includes all Schumpeterian types of innovation (new products or services, new processes or methods of production, new ways of organization, new markets, new sources of supply, and new marketing methods)[22] of both manufacturing and service firms. In addition, we have differentiated between patented and non-patented innovations and between domestic and imported ones, the latter included only when the importer was the pioneer in implementing them, at least in the UK.

One reason to distinguish between patented and non-patented innovations is their difference in nature. For instance, some innovations cannot inherently be patented and, according to our data, patented

[22] Strictly speaking, Schumpeter established only five types of innovation as he considered marketing innovations to be a kind of process innovation; but he clearly granted a singularity to the former by saying that a new process "can also exist in a new way of handling a commodity commercially" (Schumpeter, 1934, p. 66). Thus, in our classification we have differentiated new industrial processes from new marketing methods, in the same way as Ruef (2002, p. 436).

innovations are clearly more complex technically than non-patented ones. Hence, it seems interesting to test whether there is a differential effect of each type of innovation on firm survival. Of course, the matter is more complex as there are innovations not patented deliberately (see Cohen et al., 2000). In any case, the most important concern for us is not whether the innovations are patented or not, but rather to take both patented and non-patented significant innovations into account. Otherwise, if only patented (or non-patented) innovations were considered, the firms' innovation activity would be undervalued. As we have been able to gather both types, our data on significant innovations can be considered, with its limitations (see below), a comprehensive indicator of the firms' innovation activity.

In all, the database contains 523 significant innovations,[23] a sample of which is displayed in Table 3. Obviously, the information provided by the DBB is limited, so it probably does not include all the innovations introduced by the selected firms. Nevertheless, we assume that it does not omit their 'significant innovations', that is, those particularly important for the firms' performance. The average number of significant innovations by firm is 2.7, as shown in Table 2, which also shows the differences in innovativeness by groups of companies and types of innovation. But it is important to point out that the firms' innovativeness according to this indicator is far from homogeneous as it varies from not having introduced any significant innovation (10.5% of the firms) to having developed between 6 and 7 (7%) as shown in Table 4. On the other hand, the average number of significant innovations was 2.61 for the firms entering from 1816 to 1875 and 2.69 for those entering from 1876 to 1957 (see Table 2). It is certain that the contrary happens according with their median value (3 and 2 respectively), but when the significant innovations are divided by types, their medians are by and large similar for both groups (and clearly greater for the second one in non-patented innovations). In brief, the firms entering before 1875 do not seem to have had advantages in adopting innovations compared to those entering later on.[24] That is, an automatic positive relation between significant innovations and survival does not seem plausible a priori for our data.

The significant innovations are arguably the most important ones, but they are very few compared to all the innovations the firms have developed throughout their lifetime. Although mostly incremental, these other innovations may have been on the whole more important for the firms' performance than the few significant (radical in some cases) ones, as has been discussed in Section 2. Thus, it is worth including them in the analysis. There is not a source from which to obtain that information, but the overall number of patents applied for by the selected firms can be taken as a rough measure of their more ordinary (incremental) innovative effort. This can be maintained on the basis that the great majority of patents reflect minor inventions and that many of them are never implemented. In any case, most of them reflect at least certain innovation activity, and even those not implemented may be of some help for later technical developments. It is certain, though, that some patents reflect major inventions, but they are a very small proportion of all the patents registered (e.g., Pakes, 1986; Cohen and Levin, 1989; Trajtenberg et al., 1997), no more than 1% according

Table 3
Illustrative sample of the significant innovations recorded.

Company (business leader)	Brief description of the innovation	Type of innovation	Patented/Non-patented	Year
Thomas Cook & Son (Thomas Cook)	Introduction of the modern concept of travel agency.	New product	Non-patented	1841
Antony Gibbs & Sons (Henry Gibbs)	Agreement on the guano trade signed between Anthony Gibbs & Sons and the Peruvian Government with the subsequent trading monopoly secured for almost all the world.	New source of supply	Non-patented	1842
Huntley & Palmers Ltd (George Palmer)	Setting up of the first continuously running biscuit machinery in the world.	New process	Non-patented	1846
Henry Bessemer & Co (Henry Bessemer)	Invention of the first steel converter.	New process	Patented	1856
Cable & Wireless Ltd (John Pender)	Laying of the first transatlantic telegraphic cable, achieved by the entrepreneurial vision of John Pender supporting Cyrus Field.	New market	Non-patented	1866
C E Heath & Co (Cuthbert Heath)	Development of various radical innovations, such as covering the loss of profits in the aftermath of a fire or the introduction of burglary insurance, revolutionizing the insurance sector.	New product	Non-patented	1885
John Lewis Partnership (John Lewis)	New concept of partnership –implying transferring of property to the employees and other radical changes– ideated to be implemented in his department stores.	Organizational innovation	Non-patented	1918
Ferranti Ltd (Sebastian De Ferranti)	Development of one of the most successful audio-frequency transformers for wireless.	New product	Patented	1923
Penguin Books (Allen Lane)	With Penguin Books, Lane revolutionized book publishing by mixing low prices and selling outside the customary market for books.	Marketing innovation	Non-patented	1935
British Petroleum Co (John Cadman)	The vision of Cadman led to the search for oil in the UK, resulting in the first discovery in 1939.	New source of supply	Non-patented	1939

[23] Their distribution according with Schumpeter's typology is: 217 product innovations (41.5%), 144 process innovations (27.5%), 71 marketing innovations (13.6%), 65 organizational ones (12.4%), and 26 new sources of supply and new markets (5%). Regarding the second classification criterion, 194 (37%) were patented, while 329 (63%) were not. Thirdly, only 80 (15%) innovations were imported from abroad, so the great majority of them (85%) had domestic origin. This indicates –not surprisingly– a very low foreign technological dependence of the British business elite. For a more detailed analysis of the 523 innovations, see Ortiz-Villajos (2017).

[24] This is not surprising given that breakthrough innovations are mostly introduced around the entry date. In any case, all the firms in our database have had the possibility of surviving throughout at least five decades up to 2013, so all them have had great chances to innovate. Klepper and Simons (2005) have found a positive relation between early entry and innovation, but their study is not comparable with ours as they focus on companies specialized in four specific products competing between them.

Table 4
Firms' distribution by significant innovations and total patent applications.

	Firms entering in 1816–1875		Firms entering in 1876–1957		All firms	
	Number	%	Number	%	Number	%
Significant innovations by firm						
0 innovations	12	14.3	9	7.8	21	10.5
1–3 innovations	45	53.6	76	65.5	121	60.5
4–5 innovations	24	28.6	20	17.2	44	22.0
6–7 innovations	3	3.6	11	9.5	14	7.0
All firms	84	100.0	116	100.0	200	100.0
Total patent applications by firm						
0 patents	24	28.6	26	22.4	50	25.0
1–20 patents	25	29.8	31	26.7	56	28.0
21–100 patents	15	17.9	22	19.0	37	18.5
101–1000 patents	16	19.0	20	17.2	36	18.0
1001-10,000 patents	3	3.6	14	12.1	17	8.5
More than 10,000 patents	1	1.2	3	2.6	4	2.0
All firms	84	100.0	116	100.0	200	100.0

to several studies (e.g., Arts et al., 2012; Squicciarini et al., 2013; Verhoeven et al., 2013). In addition, the total number of patents is an aggregate indicator in which a radical innovation has the same weight as an incremental one. Hence, if the latter represent more than 99% of the patents, the overall number of patents not weighted by their value can more plausibly be taken as an indicator of the firms' incremental innovation.

In order to obtain this indicator we have resorted to the historical database of the European Patent Office (Espacenet), which contains information about the patents registered worldwide from 1836 to this day. Thus, the total number of patents registered by each of the selected firms from about 1836–2011 has been used as the indicator of their incremental innovation activity.[25] As shown in Table 2, the average number of patent applications by firm is 1,463,[26] much bigger than the average of significant innovations (2.7). But, as happens with the latter, the selected firms' innovativeness in terms of the overall number of patents is very variable, the range going from not having any patent to having more than 10,000 (see Table 4).[27] In addition, the firms entering in the second period (1876–1957) registered on average more patents than those entering before 1876 (see Table 2). Hence, a necessarily positive relation (a problem of endogeneity) between innovation and survival can neither be inferred a priori from this second innovation indicator.

4.2. Control variables

Many studies have found a positive effect of firm size on the probability of survival (e.g., Evans, 1987; Ericson and Pakes, 1995; Geroski, 1995; Cefis and Marsili, 2005), so we have controlled for this factor in our analysis. As we are analyzing long-lasting companies, the initial size is less relevant than the size they achieved later on given that the former does not reflect the firm's ability to adapt to changing conditions. Hence, the specific variable used here is the maximum size achieved[28] by the firms in terms of number of employees; the 'total world employment' (Pavitt, 1984, p. 345), to be more precise. There are important differences in size among the selected firms (from fewer than 1,000 employees to more than 50,000),[29] the average being 23,886 employees (Table 2). This is another sign of the outstanding performance of the firms under study as very few companies anywhere achieve such dimensions. In fact, 'fewer than 10 per cent of new organizations ever grow on any dimension, and fewer than 4 per cent of new organizations add more than 100 employees during their lifetimes' (Shane, 2003, p. 6).

The international dimension of the firm −measured either by its exporting activity or by its multinational presence– has also been found influential on business survival by several studies, although with conflicting results (e.g., Esteve-Pérez et al., 2004, 2008; Giovannetti et al., 2011). In order to control for this factor, we have included two dummy variables: one distinguishing between exporting (value 1) and non-exporting companies (value 0) and the other between firms with foreign branches (multinationals)[30] (value 1) and those only established in Britain (value 0).

Corporate Social Responsibility (CSR) has received increasing attention in the last years both from business and academic spheres. One of the reasons is the perception of its positive effect on business stability and performance, although the empirical evidence is mixed (Orlitzky, 2008; Carroll and Shabana, 2010). Most studies on the matter have focused on financial performance rather than on business survival, but it is worth exploring whether the latter is influenced by CSR. To control for this, we have included a dummy variable which takes the value one for the firms with an outstanding concern for their employees and/or their social environment and zero otherwise.

Business tradition or previous experience has been considered as a factor possibly influencing survival by several studies (e.g., Carroll et al., 1996; Klepper, 2002; Thomson, 2005). Some of our firms had no tradition at the time of entry, while others did, so we have considered it relevant to include this factor as another control variable. In particular, the variable included is the number of years of family business tradition before entry (in logarithms), the average being 29.7 years, with a slight variation between manufacturing and services (Table 2).

In addition to firm-level variables, business survival literature has also paid attention to the personal characteristics of the business leaders/founders as factors influencing the firms' longevity. Thus, we have also included seven of those features as control variables in our analysis. Namely, the business leader's age at the time of founding (or entering) the company; whether he was the founder or not; whether his previous activity was in a similar sector to that of the firm; whether he had college studies or not; whether he was trained through an apprenticeship; whether he was an inventor or not; and whether he came from a high social background or not. All the mentioned variables are defined as dummies except the first one, age at entry, which has been taken in logarithms.[31] The empirical literature has found conflicting

[25] When the number of patents registered by one firm is very high −more than 1,000 or so–, the figure obtained is approximate because in those cases the on-line database (Espacenet) does not easily allow us to go through all the patents in order to detect possible duplicates.

[26] There being a great difference between manufacturing (2,026 patents) and services (149 patents). The median value (18 patents for the whole set of firms) also reflects a great difference between industries: 38 patents for manufacturing and only 1 for services (Table 2).

[27] Given the high variation in the number of patents among firms, in order to soften such heterogeneity we have taken this variable in logarithms. In fact, this variable follows a log-normal distribution.

[28] The usual alternative to the initial size as predictor of the probability of survival is the current size (e.g., Mata et al., 1995; Esteve-Pérez et al., 2004; Cefis and Marsili, 2005; Tsvetkova et al., 2014), but it is not fitting (neither available) in our case as we do not have a panel data set. Thus, in the absence of a better alternative, we decided to use the maximum size because not including any size variable in the model would have been worse from the point of view of the econometric modeling given the great range of sizes among our selected firms.

[29] Because of the great heterogeneity between the smallest and the biggest company, we have taken this variable in logarithms as with the previous one.

[30] An alternative indicator for the firm's multinational presence is its Foreign Direct Investment (FDI), which is the one used by Giovannetti et al. (2011).

[31] This will allow us to capture a possible non-linear effect of the founder/leader's age on business survival as has been frequently noticed for other performance indicators (Shane, 2003, pp. 89–91). Another way to capture this effect is by including both the age and the age squared in the model (see Ugur et al., 2016, Table 1, for some references on this).

results in relation with most of these variables (e.g., Vivarelli and Audretsch, 1998; Klepper, 2002; Headd, 2003; Arribas and Vila, 2007; Saridakis et al., 2008), so we aim to add some new evidence in one way or the other.

4.3. Empirical model

The dependent variable in our analysis is the firm's longevity measured in years from foundation/entry to exit up to 2013 (see Section 3 for details). If $LONGEVITY \geq 0$ denotes the duration of a company, the cumulative distribution function of the variable is defined as:

$$F(t) = \text{Prob}\,[LONGEVITY \leq t]$$

for $t \geq 0$, where t is a specific value of *LONGEVITY*. The 'survivor function' of the company is defined as:

$$S(t) = 1 - F(t) = \text{Prob}\,[LONGEVITY > t]$$

which measures the survival probability of the company after year t.

The final aim is to estimate the influence of innovation and the other variables previously defined on the probability of survival of the companies under study. According with this, we have opted for a parametric duration (or survival) model. A non-parametric one would be less fitting in our case because such models are more suitable when not much is known about the sample and covariates, reason why these models do not have a structure specified a priori. That is, they make no assumptions about the probability distribution of the endogenous variable and the number of parameters; and the nature of their coefficients is very flexible. For instance, non-parametric methods are appropriate when using ranked variables with a not precise numerical interpretation, as when assessing preferences. In our case, all the variables are continuous or dummies, none of them being ordinal.[32] Another possibility would be a semi-parametric model, like the Cox proportional hazard one. But this is neither useful for us because the hazard of exit of our companies for different values of the independent variables is not proportional over time (see Appendix C),[33] this being a basic assumption of the Cox model.

In brief, the use of a parametric model is more adequate in our case because we want to test the dependency between the probability of survival and a series of measurable characteristics both of the firm and of its business leader. This relation is established by a vector of parameters which are estimated by maximum likelihood with censorship, and which reflect the partial effect of each (explanatory or control) variable on the probability of survival of the company throughout time. In the parametric duration models it is necessary to assume a specific density function for the dependent variable, normally chosen between the exponential, Weibull, log-normal, gamma or log-logistic ones (see Wooldridge, 2010 for details).

Although each study has its peculiarities, in general terms, the exponential distribution supposes a survival probability (or a hazard of exit) constant throughout time, and the Weibull one, an increasing or decreasing probability of survival (or hazard of exit) with time, depending on the value of one of the parameters characterizing that distribution. At first glance, the two mentioned behaviors do not seem plausible for our data (see Tables 1 and 2), but we have checked this statistically. Following Cleves et al. (2016), various simple contrasts based on the characteristic parameters of the gamma distribution $-k$ and *Log (beta)*– have been made, them providing evidence against the use of both the exponential and the Weibull distributions in all our estimations.[34] In fact, our dependent variable (Longevity) follows a gamma (*k, beta*) distribution, with a p-value of 0.09 at 5% and 1% of significance.

But the gamma is very similar to the log-normal distribution (except in the width of the tails), and both are equally used in many empirical applications for several reasons: both are non-negative and positively skewed and they have a constant coefficient of variation (Fu and Moncher, 2004); they have similar shapes (see Cho et al., 2004); both of them are useful when the dependent variable is skewed to the right, as happens with ours, which has an asymmetry coefficient of 0.36; and it is well known that as the k parameter increases, the gamma distribution converges to a log-normal (see Johnson et al., 1994). An advantage of the log-normal is that it is easy to understand as it is related to the normal one and fits very well data with large skewness. In addition, it is slightly more stable than the gamma in presence of outliers in the sample, as is our case, where there are, for instance, a few companies with more than 50,000 employees or with more than 10,000 patents. But it has the disadvantage that its coefficients need volatility adjustment, although this problem can be solved by calculating the parameters' standard errors in a robust way, as we have done. In brief, both the gamma and log-normal distributions seem to be suitable for the present case. In fact, the results obtained to predict the expected value of the endogenous variable and the profile of the resultant residuals confirm that both are adequate and very similar. As it is difficult to discriminate between them (see subsection 5.1), we have used both in the analysis.

As we do not have information from 2013 onwards, we cannot observe the complete duration of the companies that continued in operation after that year, so our data are right-censored to 2013.[35] Thus, it is necessary to define a censoring variable. In this case, we have defined a dummy which takes the value one if the observed duration is complete (firms exited before 2013) and zero otherwise.

5. Econometric analysis and results

This section is divided in three parts. Subsection 5.1 explains the contrasts used to discriminate between the log-normal and the gamma distributions. Subsection 5.2 presents the results of our estimations. Firstly, to get the general pattern, the results for all the companies of the data set are presented (Table 5). Then, in order to control for industry differences, we show the results for the manufacturing firms from one side (Table 6) and for the service ones from the other (Table 7). All the three estimations include four different specifications depending on the level of disaggregation of the significant innovations: (1) without disaggregation, and disaggregated (2) by Schumpeterian forms, (3) by patented and non-patented and (4) by domestic and imported. In each specification, we have included the estimations according with both the log-normal and the gamma distributions. The tables show only the preferred models.[36] The complete ones, estimated

[32] In addition, in non-parametric models, the consistency of the maximum likelihood estimator of the model's parameters depends on the sample size, which must be sufficiently large, certainly larger than ours, even if the standard errors of the parameters are calculated in a robust way as we have done. For a useful memorandum about non-parametric estimation of duration models, see Zhang (2003).

[33] Appendix C includes various pairs of smoothed hazard functions over time, each one corresponding to a different value of a covariate of the model (e.g., being a multinational company versus an only national-based one). When the two curves are not parallel, as happens in our case, the hazard rate is not proportional over time and, consequently, the Cox proportional hazard model is not adequate (see, for example, Cleves et al., 2016).

[34] The result of the contrast of the null hypothesis that the parameter $k = 1$ against the alternative that $k \neq 1$, confirms that our data do not support the Weibull distribution. And the result of the joint contrast that $k = 1$ and *Log (beta)* $= 0$, with a p-value = 0.000, goes against the hypothesis of a constant hazard of exit over time; that is, against the exponential distribution.

[35] As the significant innovations have been recorded from the DBB, published in 1984-86, the information on this variable is previous to c. 1985. Thus, we have estimated the models also right-censored to 1985, assuming that there can be relevant missing information on the companies' innovation activity from that year to 2013. The results of these models are quite similar to those right-censored to 2013 (this being an indication of the long-lasting effect of innovation), so we have not included them in the tables. The few significant differences will be pointed out opportunely.

[36] These are achieved by the usual procedure. Firstly, the less significant variable (the one with the highest p-value) of the complete model is eliminated; then, the model without that variable is re-estimated and the less significant variable, eliminated; and so on. This iterative process ends when all the variables are individually significant at least at the 10% level. In addition, the information criteria (AIC and BIC) are used to discriminate adequately between the complete model and the preferred (or final) one.

Table 5
Results of the log-normal and gamma duration models for business survival (MLE): All firms (A) (preferred models).

	A1		A2		A3		A4	
	Lognormal	Gamma	Lognormal	Gamma	Lognormal	Gamma	Lognormal	Gamma
Constant	5.786***	5.785***	5.736***	5.813***	5.630***	5.671***	5.830***	5.817***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Significant Innovations (SI)	0.043**	0.034*	–	–	–	–	–	–
	(0.029)	(0.094)						
SI by Schumpeterian forms:								
New Product	–	–			–	–	–	–
New Process	–	–	0.106***	0.094***	–	–	–	–
			(0.002)	(0.006)				
Organizational	–	–			–	–	–	–
Marketing	–	–			–	–	–	–
New Market	–	–			–	–	–	–
New Source	–	–			–	–	–	–
Patented/Non-patented SI:								
Patented SI (in log)	–	–	–	–			–	–
Non-patented SI (in log)	–	–	–	–	0.153**	0.114	–	–
					(0.033)	(0.106)		
Domestic/Foreign SI:								
Domestic SI	–	–	–	–	–	–	0.044**	0.035*
							(0.036)	(0.090)
Imported SI	–	–	–	–	–	–		
Total patent applications (in log)								
Firm's size (in log)	0.088***	0.083***	0.097***	0.089***	0.088***	0.085***	0.090***	0.084***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Multinational	0.194**	0.193**	0.199**	0.190***	0.186**	0.181**	0.200**	0.200***
	(0.015)	(0.012)	(0.011)	(0.009)	(0.022)	(0.022)	(0.013)	(0.009)
Exports								
Outstanding CSR								
Family business tradition (in log)	0.042**	0.038**	0.034*	0.035*	0.035*	0.035*	0.041**	0.038**
	(0.034)	(0.041)	(0.084)	(0.058)	(0.072)	(0.067)	(0.037)	(0.046)
Business leader's personal traits:								
Age at founding (in log)	−0.727***	−0.677***	−0.722***	−0.685***	−0.680***	−0.645***	−0.743***	−0.685***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Founder								
Similar previous sector								
College studies								
Apprenticeship								
Inventor								
High social background								
No of observations	200	200	200	200	200	200	200	200
Sigma	0.502		0.497		0.502		0.502	
	(0.021) se		(0.027) se		(0.026) se		(0.028) se	
K		0.451		0.520		0.434		0.461
		(0.033)		(0.036)		(0.085)		(0.051)
Log (beta)		−0.762		−0.789		−0.756		−0.764
		(0.000)		(0.000)		(0.000)		(0.000)
LogL (optimum)	−146.465	−144.594	−143.954	−141.739	−145.988	−144.490	−146.598	−144.670
AIC	306.930	305.180	301.910	299.480	305.980	304.990	307.200	305.340
BIC	330.020	331.570	324.990	325.870	329.060	331.380	330.290	331.720

Notes: MLE: exact maximum likelihood estimation with robust standard errors. *P*-value in brackets (except for the *Sigma* parameter, for which the figure in brackets is the standard error). *, **, and *** denote significance at the 10% ($p < 0.1$), 5% ($p < 0.05$) and 1% ($p < 0.01$) respectively. *Sigma* is the parameter which characterizes the standard error (se) in a log-normal distribution. *K* and *Log (beta)* are respectively the shape and the scale parameter in a gamma distribution. *LogL (optimum)* is the value of the likelihood function in the optimum (in logarithms). AIC is the Akaike Information Criterion. BIC is the Bayesian Information Criterion.

with all the explanatory and control variables, can be consulted in Appendix B. In order to be more specific about the effect of the variables, we have calculated −from the models in Tables 5 to 7– the predicted difference in the firm's longevity (in years) when, *ceteris paribus*, a variable takes the median value[37] compared to its opposite (or its maximum or minimum value when the variable is not a dummy) (Table 8). Lastly, some evidence on the robustness of the analysis is presented in subsection 5.3, firstly, by estimating the same duration models for the firms entering before and after 1875 (Table 9) in order to test a potential endogeneity problem; and, secondly, by checking both graphically and statistically the properties of the Cox-Snell residuals resultant from the models using the log-normal distribution (Fig. 2 and Table 10).

5.1. Discrimination between the log-normal and the gamma distribution

As has been said, our data seem a priori to fit well both the gamma and the log-normal distributions, but is it possible to discriminate in favour of one or the other? In order to check this, five discriminatory measures have been calculated.

The two parameters designed as *sigma* (the standard error) and k (the shape parameter) are characteristic of the log-normal and the gamma distributions respectively. If, according with the p-value, the null hypothesis that k is equal to zero against the alternative that it is different from zero is not rejected, then the result of this contrast suggests that the log-normal distribution would be more adequate in our

[37] The median is a better reference than the mean when the variables are highly dispersed – as happens in the present case (see Table 2) – because, contrary to the mean, the median is not affected by the presence of a few firms with a very high (or low) value in any of the control variables.

Table 6
Results of the log-normal and gamma duration models for business survival (MLE): Manufacturing firms only (B) (preferred models).

	B1		B2		B3 & B4[(a)]	
	Lognormal	Gamma	Lognormal	Gamma	Lognormal	Gamma
Constant	5.383***	5.650***	5.259***	5.512***	5.383***	5.650***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Significant Innovations (SI)			–	–	–	–
SI by Schumpeterian forms:						
New Product	–	–			–	–
New Process	–	–	0.083***	0.070**	–	–
			(0.010)	(0.035)		
Organizational	–	–			–	–
Marketing	–	–			–	–
New Market	–	–			–	–
New Source	–	–			–	–
Patented/Non-patented SI:						
Patented SI (in log)	–	–	–	–		
Non-patented SI (in log)	–	–	–	–		
Domestic/Foreign SI:						
Domestic SI	–	–	–	–		
Imported SI	–	–	–	–		
Total patent applications (in log)	0.029*	0.028*			0.029*	0.028*
	(0.080)	(0.085)			(0.080)	(0.085)
Firm's size (in log)	0.080**	0.069**	0.114***	0.101***	0.081**	0.069**
	(0.046)	(0.048)	(0.000)	(0.001)	(0.046)	(0.048)
Multinational						
Exports						
Outstanding CSR	0.211***	0.154*	0.186**	0.129	0.211***	0.154*
	(0.006)	(0.065)	(0.014)	(0.143)	(0.006)	(0.065)
Family business tradition (in log)						
Business leader's personal traits:						
Age at founding (in log)	−0.548***	−0.563***	−0.582***	−0.589***	−0.548***	−0.563***
	(0.005)	(0.001)	(0.002)	(0.001)	(0.005)	(0.001)
Founder						
Similar previous sector						
College studies						
Apprenticeship						
Inventor						
High social background						
No of observations	140	140	140	140	140	140
Sigma	0.457		0.454		0.457	
	(0.033) se		(0.030) se		(0.036) se	
K		0.487		0.478		0.487
		(0.061)		(0.138)		(0.060)
Log (beta)		−0.863		−0.863		−0.864
		(0.000)		(0.000)		(0.000)
LogL (optimum)	−91.917	−91.128	−90.942	−89.620	−91.917	−90.128
AIC	195.830	194.260	193.880	193.240	195.830	194.260
BIC	213.490	214.850	211.530	213.830	213.480	214.850

Notes: see Table 5. [(a)] B3 and B4 preferred models are coincident.

case (see Cleves et al., 2016). According with this, for instance, the log-normal distribution would be preferable to the gamma in the four models including all the firms (Table 5).

The other three measures provided are very usual in the estimation by maximum likelihood of any econometric model. The first one (*LogL*) is the value of the likelihood function in the optimum (in logarithms), which in our case is always better −although very slightly– for the models based on the gamma distribution. The second one is the Akaike information criterion (AIC), which discriminates in favour of the gamma distribution for the models including all the companies or the manufacturing ones (Tables 5 and 6) and in favour of the log-normal for the other two cases (Tables 7 and 9). The third one is the Bayesian information criterion (BIC), which discriminates in favour of the log-normal distribution in the first two groups of models (Tables 5 and 6) and in favour of the gamma in the second ones (Tables 7 and 9). In any case, the numerical value of the three mentioned discriminatory criteria is always very similar.

In sum, the mentioned measures and the coefficients and statistical significance of the models estimated assuming the log-normal and gamma distributions, displayed in Tables 5–9, confirm the similarity and adequacy of both of them. In some cases and marginally it is possible to discriminate in favour of one or the other, and that could be useful depending on the objective of the analysis. But on the whole and for the present case both of them seem valid. As famously remarked, when working with real data, "all models are wrong" (Box, 1976, p. 792). Hence, for reasons of transparency (and because the estimation based on the gamma does not converge in one specification),[38] we have calculated and presented our estimations according with both distributions.

5.2. Results of the duration models estimated

A first piece of evidence from the analysis of the *overall set of firms* (Table 5) is that the innovation activity measured by significant innovations (SI) in aggregated terms (specification A1) is positively and

[38] The maximum likelihood estimation of Model C2 using the gamma distribution does not converge, while it does when using the log-normal (see Table 7). It must be highlighted that we have used both Stata and Gretl to estimate the models and both programs give the same exact results in all cases.

Table 7
Results of the log-normal and gamma duration models for business survival (MLE): Service firms only (C) (preferred models).

	C1		C2		C3		C4	
	Lognormal	Gamma	Lognormal	Gamma$^{(a)}$	Lognormal	Gamma	Lognormal	Gamma
Constant	7.326***	7.268***	4.999***		6.555***	6.430***	4.703***	4.708***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Significant Innovations (SI)	0.090*	0.090*	–		–	–	–	–
	(0.064)	(0.067)						
SI by Schumpeterian frms:								
New Product	–	–	0.128*		–	–	–	–
			(0.084)					
New Process	–	–			–	–	–	–
Organizational	–	–			–	–	–	–
Marketing	–	–	−0.187**		–	–	–	–
			(0.047)					
New Market	–	–			–	–	–	–
New Source	–	–			–	–	–	–
Patented/Non-patented SI:								
Patented SI (in log)	–	–	–				–	–
Non-patented SI (in log)	–	–	–				–	–
Domestic/Foreign SI:								
Domestic SI	–	–	–		–	–	0.088*	0.087
							(0.100)	(0.157)
Imported SI	–	–	–		–	–	0.372**	0.327
							(0.017)	(0.146)
Total patent applications (in log)								
Firm's size (in log)			0.118***		0.080*	0.079*	0.107***	0.109**
			(0.003)		(0.068)	(0.051)	(0.009)	(0.017)
Multinational	0.561***	0.573***	0.441***		0.491***	0.526***	0.342**	0.348*
	(0.000)	(0.000)	(0.002)		(0.001)	(0.001)	(0.033)	(0.076)
Exports	−0.341*	−0.342*	−0.415**		−0.332**	−0.297*		
	(0.059)	(0.061)	(0.017)		(0.046)	(0.067)		
Outstanding CSR								
Family business tradition (in log)	0.081*	0.086**						
	(0.058)	(0.034)						
Business leader's personal traits:								
Age at founding (in log)	−0.985***	−0.949***	−0.608**		−0.870***	−0.808***	−0.648**	−0.645**
	(0.003)	(0.003)	(0.012)		(0.003)	(0.005)	(0.013)	(0.016)
Founder								
Similar previous sector			0.361*				0.537**	0.523
			(0.074)				(0.049)	(0.173)
College studies								
Apprenticeship								
Inventor								
High social background			0.438**		0.387*	0.421**	0.377*	0.384
			(0.034)		(0.080)	(0.030)	(0.077)	(0.104)
No of observations	60	60	60		60	60	60	60
Sigma	0.549		0.504		0.553		0.524 (0.047) se	
	(0.062) se		(0.048) se		(0.057) se			
K		0.331				0.570		0.060
		(0.307)				(0.123)		(0.941)
Log (beta)		−0.652				−0.706		−0.652
		(0.000)				(0.000)		(0.000)
LogL (optimum)	−47.732	−47.374	−42.881		−40.099	−47.300	−44.807	−44.803
AIC	109.460	110.750	107.760		110.100	110.590	107.610	109.610
BIC	124.120	127.500	130.800		124.760	127.340	126.460	130.550

Notes: see Table 5. [(a)] The MLE estimation does not converge in this case.

significantly (at the 5% level with the log-normal and at the 10% with the gamma) related with the probability of business survival. It shows an innovation premium in line with the findings by Cefis and Marsili (2006) and other studies (see Section 2). When the significant innovations are disaggregated by types, their relevance is confirmed, but in a more nuanced way as not all types are found to be influential. In particular, only new process innovations (specification A2), non-patented (A3) and domestic ones (A4) seem to affect positively and significantly (between the 1% and the 10% level depending on the type of innovation and the distribution used) the probability of survival. According with our calculations, a company with the median amount of significant innovations of the aforementioned types would survive, *ceteris paribus*, between 6.4 and 9.4 years more than a firm without any one, looking jointly at the estimations based on the log-normal and the gamma distributions (Table 8). On the contrary, the innovation activity measured by total patent applications shows no relation with the firms' survival probability in any of the four specifications. According with this, it could be said that for the overall set of firms, survival depends more on important innovations (SI) than on incremental ones (total patents).

That new process, non-patented and domestic significant innovations are the most influential types of innovation on business survival compared with their corresponding counterparts (i.e., new product, patented and imported innovations) is an interesting finding, but how to explain it? This would require a detailed analysis of the innovations and companies, which exceeds the object of the present study. Some hypothetical explanations can be suggested, though. The influence of process innovations could be explained by their increasing importance over time for the competitiveness of companies relative to product ones, as the product life cycle theory indicates (Vernon, 1966; Utterback and Suárez, 1993). Klepper and Simons (2005, p. 41) have found some empirical evidence on the

Table 8
Predicted difference in the firm's longevity when the independent variable takes the median value compared to its opposite (maximum or minimum) value (from the models in Tables 5–7)[(a)].

Independent variable	Specification	Value of the independent variable		Difference in survival time in favor of the median firm (years)	
		Median	Opposite/max-min	Log-normal	Gamma
All firms (A)					
Significant Innovations (SI)	A1	2	0	7.24	6.38
New process SI	A2	0	1	−9.43	−9.27
Non-patented SI (in log)	A3	0.69	0	8.91	7.45
Domestic SI	A4	2	0	7.71	6.79
Firm's size (in log)	A1	8.62	3.91	30.06	31.94
Firm's size (in log)	A2	8.62	3.91	34.46	32.56
Firm's size (in log)	A3	8.62	3.91	30.06	32.28
Firm's size (in log)	A4	8.62	3.91	31.37	32.82
Multinational	A1	yes	no	15.68	17.29
Multinational	A2	yes	no	12.52	12.24
Multinational	A3	yes	no	15.07	16.24
Multinational	A4	yes	no	16.47	18.20
Family business tradition (in log)	A1	2.77	0	9.65	9.99
Family business tradition (in log)	A2	2.77	0	7.55	8.81
Family business tradition (in log)	A3	2.77	0	8.14	8.89
Family business tradition (in log)	A4	2.77	0	9.71	9.92
Age at founding (in log)	A1	3.37	4.04	34.50	35.94
Age at founding (in log)	A2	3.37	4.04	32.60	35.20
Age at founding (in log)	A3	3.37	4.04	32.68	34.54
Age at founding (in log)	A4	3.37	4.04	35.81	36.95
Manufacturing firms only (B)					
New process SI	B2	0	1	−6.39	−6.06
Total patent applications (in log)	B1, B3, B4	3.65	0	7.84	8.50
Firm's size (in log)	B1, B3, B4	8.67	5.30	18.55	18.14
Firm's size (in log)	B2	8.67	5.30	23.51	24.07
Outstanding CSR	B1, B3, B4	no	yes	−18.37	−14.60
Outstanding CSR	B2	no	yes	−15.13	−11.5
Age at founding (in log)	B1, B4	3.33	3.97	23.08	24.49
Age at founding (in log)	B2	3.33	3.97	22.95	26.23
Age at founding (in log)	B3	3.33	3.97	36.15	26.36
Services firms only (C)					
Significant Innovations (SI)	C1	2	0	15.14	16.57
New product SI	C2	0	1	−10.30	(b)
New process SI	C2	0	1	−14.25	(b)
Domestic SI	C4	2	0	14.10	14.16
Imported SI	C4	0	1	−39.37	−38.68
Firm's size (in log)	C2	8.52	3.91	31.50	(b)
Firm's size (in log)	C3	8.52	3.91	25.90	29.87
Firm's size (in log)	C4	8.52	3.91	34.10	34.95
Multinational	C1	yes	no	48.26	43.87
Multinational	C2	yes	no	26.86	(b)
Multinational	C3	yes	no	32.69	39.95
Multinational	C4	yes	no	25.30	26.00
Exports	C1	yes	no	−37.52	−41.01
Exports	C2	yes	no	−38.68	(b)
Exports	C3	yes	no	−33.23	−33.86
Family business tradition (in log)	C1	1.84	0	12.74	14.70
Age at founding (in log)	C1	3.40	4.04	43.24	45.70
Age at founding (in log)	C2	3.40	4.04	24.33	(b)
Age at founding (in log)	C3	3.40	4.04	30.23	39.47
Age at founding (in log)	C4	3.40	4.04	29.72	29.94
Similar previous sector	C2	yes	no	22.84	(b)
Similar previous sector	C4	yes	no	36.30	36.12
High social background	C3	no	yes	−39.37	−54.42
High social background	C4	no	yes	−39.98	−24.61

[(a)] The predictions conditioned to the median value of the x's are calculated by the exp(x'b), where x is a vector of medians of the independent variables and b is the vector of parameters estimated by MLE in the convergence (see Wooldridge, 2010).
[(b)] The MLE estimation does not converge for specification C2 when the gamma distribution is assumed for the endogenous variable.

increasing attention to process innovation in a few specific industries over time. It is less clear why non-patented significant innovations are more influential than patented ones. A plausible explanation is that non-patented innovations are normally very specific to their developers and not easy to replicate, this giving them a sustained competitive advantage. On the other hand, patented innovations are replicable by definition, frequently licensed and, in any case, ever more difficult to maintain under the inventor's control, so the advantages they provide to the inventor tend to diminish over time. Thirdly, the advantages of domestic innovations compared, *ceteris paribus*, to imported ones (such as lead time, better adaptation to local conditions, or greater potentiality and versatility as their know-how belongs to the firm) seem a reasonable explanation of their greater influence on survival.

In relation with the other five characteristics of the firm included in the model, the firm's size appear to have a positive and highly significant effect (at the 1% level) on the probability of survival in all the four specifications both with the log-normal and the gamma distributions, the median company surviving some 30 years more than the smallest one

Table 9
Results of the log-normal and gamma duration models for business survival (MLE): Firms entering in 1816–1875 (D) and in 1876–1957 (E) (preferred models).

	Entry period: 1816–1875				Entry period: 1876–1957			
	D1		D2		E1		E2	
	Lognormal	Gamma	Lognormal	Gamma	Lognormal	Gamma	Lognormal	Gamma
Constant	3.630***	3.811***	3.637***	3.791***	5.444***	5.191***	5.564***	5.173***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Significant Innovations (SI)			–	–	0.089***	0.086***	–	–
					(0.002)	(0.003)		
SI by Schumpeterian forms:								
New Product	–	–			–	–	0.067*	0.076**
							(0.089)	(0.047)
New Process	–	–			–	–	0.196***	0.179**
							(0.003)	(0.012)
Organizational	–	–			–	–	0.140*	0.161**
							(0.072)	(0.018)
Marketing	–	–			–	–		
New Market	–	–			–	–		
New Source	–	–	0.191**	0.149	–	–		
			(0.021)	(0.120)				
Total patent applications (in log)	0.057***	0.053**	0.060***	0.057**				
	(0.003)	(0.017)	(0.002)	(0.011)				
Firm's size (in log)	0.127***	0.111***	0.126***	0.112***	0.067**	0.068**	0.055*	0.056*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.047)	(0.034)	(0.082)	(0.060)
Multinational	0.292***	0.294***	0.283***	0.284***	0.213**	0.204**	0.206**	0.192**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.033)	(0.046)	(0.030)	(0.049)
Exports	−0.401***	−0.366**	−0.417***	−0.384**				
	(0.004)	(0.017)	(0.003)	(0.013)				
Outstanding CSR								
Family business tradition (in log)					0.044*	0.045*		
					(0.067)	(0.051)		
Business leader's personal traits:								
Age at founding (in log)					−0.651***	−0.547***	−0.620***	−0.471**
					(0.000)	(0.008)	(0.001)	(0.030)
Founder								
Similar previous sector								
College studies								
Apprenticeship								
Inventor					−0.173*	−0.211**	−0.224*	−0.265**
					(0.093)	(0.047)	(0.056)	(0.024)
High social background								
No of observations	84	84	84	84	116	116	116	116
Sigma	0.408		0.405		0.463		0.435	
	(0.043) se		(0.044) se		(0.035) se		(0.033) se	
K		0.381		0.330		0.434		0.560
		(0.232)		(0.299)		(0.342)		(0.223)
Log (beta)		−0.949		−0.947		−0.843		−0.876
		(0.000)		(0.000)		(0.000)		(0.000)
LogL (optimum)	−45.058	−44.119	−44.389	−43.658	−78.010	−77.448	−77.407	−76.391
AIC	102.120	102.240	102.770	103.320	172.190	172.900	172.810	172.780
BIC	116.700	119.250	119.790	122.760	194.230	197.680	197.600	200.320

Notes: see Table 5.

(Table 8). This shows the high relevance of size for business survival in line with many other studies. Secondly, the multinational character of the firm also has a positive and highly significant influence on the probability of survival, coinciding with the findings by Giovannetti et al. (2011). In quantitative terms, a multinational would survive, *ceteris paribus*, between 12 and 18 years more than a merely national-based company (Table 8). Instead, the other international dimension, the exporting activity, shows no influence at all on business survival, contrary to the results obtained by Esteve-Pérez et al. (2004, 2008). On the other side, family business tradition before entry has a positive and significant effect on the survival probability, the median company (with 15 years of tradition) presumably surviving between 7 and 10 years more than a firm without tradition (Table 8). Thus, business tradition is a positive factor for longevity as other studies have found (Vivarelli and Audretsch, 1998; Klepper, 2002; Thomson, 2005; Fontana and Nesta, 2009). Lastly, having an outstanding CSR does not seem to affect survival.

Among the seven business leader's personal traits included in the analysis, only one −the age at founding/entry– has a significant effect (at the 1% level in all cases) on survival, negative in this case. This confirms the expected non-linear effect of this factor on the business survival probability. According with our calculations, the median company (founded by a 29-year old entrepreneur as shown in Table 2) would survive between 32 and 37 years more than one founded by the most mature entrepreneur (Table 8). This result is conflicting with some studies which have found no relation between the founder's age and firm survival (Arribas and Vila, 2007; Saridakis et al., 2008),[39] but is in line with others showing a curvilinear effect of the entrepreneur's age on business performance in general (Shane, 2003, pp. 89–91). This can be explained by the higher innovative/creative character of relatively young business leaders compared to very young or very mature ones. On the other hand, when we distinguish between business leaders that are founders and those that are not, we do not find any significant differential effect on business

[39] Headd (2003) has found that age is positive for survival in some cases, but negative in others. In any case, this study is not comparable with ours as it is focused not on the founder or key business leader but on the current owner of the company.

survival. This result suggests that, when considering only relevant business leaders (as is our case), being the founder is not what makes the difference, at least in relation with the survival of the company.

The variables related with the leaders' education –having college studies or an apprenticeship– do not seem to have any influence on business survival. This coincides with the findings of several studies (e.g., Taylor, 1999; Arribas and Vila, 2007) but conflicts with others (e.g., Headd, 2003; Saridakis et al., 2008).[40] Nor is the entrepreneur being an inventor or having a high social background relevant for the firm's probability of survival, these findings being specific contributions of our research. Lastly, having worked in a similar sector before founding/entering the company is not influential on survival either, this conflicting with other studies (Klepper, 2002; Thomson, 2005; Arribas and Vila, 2007; Fontana and Nesta, 2009). Nevertheless, this variable (pre-entry experience) becomes significant when we split our data set by sectors. The same happens with other factors –total patents, exporting activity, CSR, and social background– not found significant for the overall set of firms, as we shall show immediately.

When the same log-normal and gamma duration models are estimated only for the *manufacturing firms* of the data set, some differences appear (Table 6). First, while the SI as a whole do not seem to influence the probability of survival of this group of firms, their overall patent applications affect it positively and significantly (specification B1). This result –just the opposite of the one observed for all the firms (A1)– would indicate that in manufacturing many incremental innovations (total patents) are more important than some radical (SI) ones for business survival. The fact that patents contain technologies predominantly related with manufacturing is probably another explanation for this result. When the SI are disaggregated by patented and non-patented and domestic and imported (B3 and B4 specifications), the same result is obtained; that is, none of the SI types seem to influence survival, while total patent applications have a positive and significant effect, the median company surviving about 8 years more than a firm without any patent according with our predictions (Table 8). Nevertheless, when dividing the SI by Schumpeterian forms (B2), new process innovations seem to influence positively and significantly (at the 5% level both for log-normal and gamma models) the probability of survival. A company with one significant process innovation would survive, *ceteris paribus*, about 6 years more than a firm without any one (Table 8). This is in line with the finding by Cefis and Marsili (2005) that process innovations are the key ones for business survival in manufacturing. In this case, however, the preferred specification excludes the overall number of patents, as if they were overshadowed by the SI (radical) new process innovations.[41]

Among the other characteristics of the firm, its size appears to influence business survival positively and significantly in the four specifications (from B1 to B4) –the median company presumably surviving, *ceteris paribus*, from 18 to 24 years more than the smallest one (Table 8)–, but not the family business tradition nor the multinational character, both of which did have a positive effect for the overall set of firms (Table 5). Thus, the international expansion of the manufacturing companies –both by creating branches abroad and by exporting– does not seem to influence their survival. Instead, having an outstanding Corporate Social Responsibility (CSR) seems to produce a highly positive and significant effect on business survival in all the specifications (from B1 to B4), thus indicating that social responsibility would be particularly relevant in manufacturing. In fact, according with our estimations, a firm of that sector with outstanding CSR would survive, *ceteris paribus*, between 11.5 and 18.4 years more than one without it (Table 8).

In relation with the personal traits of the manufacturing firms' business leaders, only the age at entry seems to influence the probability of survival, the negative sign of the coefficient indicating a nonlinear relation between both variables, just as we have observed for all the firms. Likewise, the difference in survival between the median and the maximum age at entry would be between 23 and 36 years in favor of the former, as shown in Table 8.

The estimation results for the *service firms only* (Table 7) are quite different –somehow complementary– from those for the manufacturing ones. Firstly, the SI taken in aggregated terms (specification C1) appear to affect positively and significantly the probability of business survival, the predicted longevity of a firm with two SI (median value) compared with another without SI being between 15.1 and 16.6 years greater (Table 8). On the contrary, the overall patent applications show no influence at all on the longevity of the service firms. That is, although they have registered some patents during their lifetime (see Table 2), this activity does not seem to have been relevant for their survival. This could be explained by the fact that, as has been said, patents are mostly oriented towards manufacturing.

When the SI are disaggregated by Schumpeterian forms (specification C2),[42] both new product and new process innovations appear to significantly increase the probability of business survival.[43] According with our estimations, compared with a firm without any innovation, a firm with one product innovation would survive 10.3 years more, and a firm with one process innovation, 14.3 years more (Table 8). The special relevance of these two types of innovation has been also highlighted by other survival studies (Cefis and Marsili, 2005, 2006, 2012; Sharif and Huang, 2012; Børing, 2015). Marketing innovations also show a significant effect on survival, but negative. This could be explained by the fact that marketing innovations are particularly focused on the short term, but further research on the matter is needed. In fact, this result seems to conflict with other studies which have found a positive influence of marketing innovations on survival (Buddelmeyer et al., 2010; Helmers and Rogers, 2010). Nevertheless, they use a different indicator for marketing innovations (trade mark applications), so their results are not properly comparable with ours.

When we divide the SI by patented and non-patented (specification C3) none of them are significant, although the non-patented ones are close to being so.[44] On the contrary, when the distinction is between domestic and imported SI (C4), both kinds appear to influence survival positively and significantly,[45] the numerical effect of the imported ones being greater. It is worth noting that the predicted longevity of a firm with one imported SI would be some 39 years more than that of a firm without any one (Table 8). This could be indicating that the adoption of American innovations in retail and other activities by the British firms since the beginning of the twentieth century was particularly relevant for their performance.

Of the other five characteristics of the firm, four seem to influence the survival probability in this case (Table 7). Like the manufacturing companies, both firm size (specifications C2, C3 and C4) and family business tradition (C1) seem to have a positive and significant effect on business survival in services. The median company would survive between 25 and 35 years more than the smallest one, and between 12.7 and 14.7 years more than a firm without family business tradition (Table 8). In addition, the two international dimensions appear to be relevant in this sector, unlike in manufacturing. In particular, having branches abroad (being a multinational) seems to greatly improve the survival probability of the British service firms, this variable being

[40] Some studies have found a positive effect of education on firm performance when the founders' studies are differentiated by types (e.g., Colombo and Grilli, 2005). Exploring this possibility with our sample would be an interesting line for further research.

[41] When the censoring year is 1985, both new process SI and total patent applications seem to affect significantly and positively the probability of survival, indicating that both kinds of innovation are compatible. In fact, in the complete B2 specification (censored to 2013) both variables are also positive and significant (see Appendix B).

[42] In the case of Model C2, the MLE estimation assuming the gamma distribution does not converge.

[43] When the censoring year is 1985, organizational innovations also appear to have a positive effect.

[44] In fact, when the censoring year is 1985, they show a highly significant and positive effect on survival.

[45] In this case, only according with the model based on the log-normal distribution.

significant at 1% or 5% in the four specifications (from C1 to C4). The longevity of a multinational would be between 25 and 48 years greater than that of a firm not implanted abroad (Table 8). This result is in line with the finding by Giovannetti et al. (2011) that FDI has a positive effect on survival. Instead, the exporting activity shows a significant (at the 5% or 10% level) but negative effect on business survival in three specifications (C1, C2 and C3). This would indicate that providing services abroad without a stable structure in the foreign country reduces the firm's longevity. This result coincides with the findings by Giovannetti et al. (2011), but conflicts with Esteve-Pérez et al. (2004, 2008), who each have found a positive effect of the exporting activity on business survival. Finally, it is worth noting that having an outstanding CSR, which was found important for survival in manufacturing, does not seem to have any influence in services. We are not aware of other studies analyzing the effect of CSR on business survival by industries, neither have we an explanation for this finding at this moment, so it remains open to further evidence and discussion.

Among the personal traits of the business leaders of the service companies, the age at founding/entry appears to be very influential on the probability of survival in all the specifications (from C1 to C4), with a non-linear effect, just as happens with all the companies (Table 5) and the manufacturing ones (Table 6). In addition, in the case of the services group, unlike in the other two, there are two more significant factors, both of them positively affecting the probability of survival; namely, the leader having worked in a similar previous sector (specifications C2 and C4) and having a high social background (C2–C4). Companies with business leaders with any of these two characteristics would survive, *ceteris paribus*, between about 22 and 54 years more than firms with leaders lacking them (Table 8). Previous experience has also been identified as important for business survival in services (Arribas and Vila, 2007) as well as in manufacturing (Klepper, 2002; Thomson, 2005; Fontana and Nesta, 2009), while we are not aware of other survival studies analyzing the social background of the entrepreneur. Our results show that a high social position of the business leader seems to be relevant for survival in services, but not in manufacturing. This could be explained by the particular importance of social connections in services such as banking or consultancy.

5.3. Robustness of the estimated models

It could be the case that the firms entering earlier had advantages in adopting innovations compared to the firms entering later on, which automatically would result in a positive relation between innovation and survival. Although, as has been said in Section 4.1, this endogeneity problem is not suggested by the descriptive statistics (see Tables 1 and 2), we have tested it by introducing the temporal factor in the analysis. In order to do this, we have divided our data set between the firms entering during the 'golden age' of the British economy (1816–1875) and those entering from then on (1876–1957), and estimated the models for each group separately (Models D and E).

From this exercise (Table 9),[46] a problem of endogeneity cannot be inferred as the survival probability of both the firms that entered up to 1875 and those that entered from then on is positively affected by innovation, the former not showing an advantage to innovate compared to the latter. It is certain, though, that they differ in the type of innovation influencing survival, but this is reasonable and coherent with our previous findings. In the case of the firms entering in the first period (Model D), incremental innovations (total patent applications) are the most influential on survival (specification D1), as happened with the group of manufacturing firms (Table 6). This is not surprising given the prominence of manufacturing before 1875. Although smaller, a positive effect on survival of the significant innovations dealing with new sources of supply is also observable for the firms entering before 1875 (specification D2), this being reasonable because of the higher chances of finding new sources of supply in earlier times.

On the other hand, the probability of survival of the firms entering after 1876 (specifications E1 and E2) is positively affected only by significant innovations, as occurs with the overall set of firms (Table 5) and the service group (Table 7). Precisely, the greater presence of service firms among those entering after 1876 is a plausible explanation of this. When the significant innovations are divided by Schumpeterian types (specification E2), new processes and new products appear to positively influence the survival probability of firms entering after 1875, as happens with the overall set and/or the group of service firms (Tables 5 and 7). In addition, the development of new organizational methods appear to positively affect the survival of that group of firms (and not the other ones), this being reasonable given that organizational innovations increased their relevance since the last decades of the nineteenth century.

In relation with the other firm's characteristics, the main difference between both groups is that the exporting activity seems to be negative for the survival probability of the companies entering in 1816–75 (specifications D1 and D2) and indifferent for those entering later on (E1 and E2). This is in line with the conflicting results on the effect of the exporting activity on business survival obtained by previous research (*vid. supra*), but seems to indicate quite clearly that exporting was particularly negative for the survival of firms entering before 1875. This could be explained by the high transport costs previous to the first great globalization. On the contrary, having branches abroad and a bigger size seem to be positive factors for survival in both groups, as happens with the overall set of firms (Table 5). In relation with the personal traits of the founder/business leader, the most striking result is that none of them seem to have any influence on the survival probability of the firms entering in the first period (1816–1875). This could be indicating, as seems reasonable, that the founder/business leader's influence decreases with the age of the company. In relation with the firms entering after 1875, two features appear to significantly affect business survival. The first one is the age at entry, which has a non-linear effect as happens in all the previous estimated models (Tables 5–7). The second one is the business leader being an inventor, which has a negative effect on survival. This could be explained by the increasing relevance of managerial compared to technical conditions of the business leader since the last decades of the nineteenth century (Chandler, 1977), together with the fact that inventors are frequently not the best entrepreneurs.

To sum up, the analysis of the firms by periods of entry (Table 9) does not reflect an endogeneity problem between innovation and longevity and confirms by and large −with some explainable differences– the results of our previous estimations (Tables 5–7) by identifying innovation, firm size, multinational presence and the business leader's age at entry as the main factors influencing business survival. Hence, it gives robustness to our analysis.

Another way to test whether our estimations are adequate is by checking certain properties of the Cox-Snell residuals resultant from the estimation of the log-normal models. This can be made graphically or statistically. The former way implies the graphic representation of the relation between the dependent variable (longevity) in logarithms and the residuals resulting from the model, called Cox-Snell residuals, also in logarithms. If the scatter graph is well adjusted to the 45° line from the origin, then it can be said that the estimation is valid. According with this, Fig. 2, which shows the Cox-Snell residuals of the first specification of all the (log-normal) estimated models, confirms their adequacy.[47]

The statistical way to test the validity of the models is by checking

[46] For reasons of space, only the results of specifications 1 and 2 have been included in the Table. All the results are available upon demand.

[47] This can be also said for Model C1, although in this case the residuals' dispersion is greater than in the rest of the models because of the fewer number of service companies.

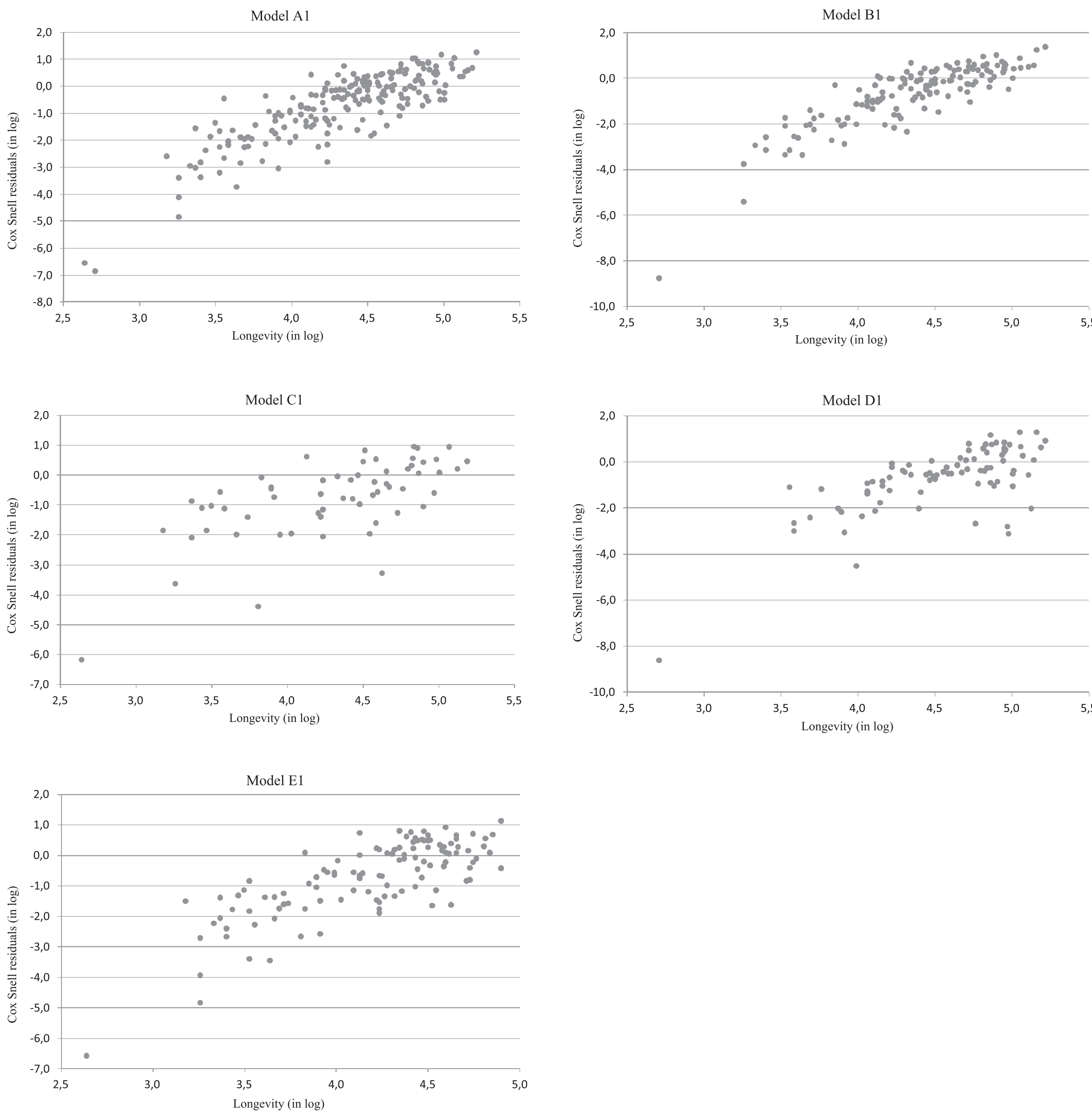

Fig. 2. Relation between Cox-Snell residuals and longevity in specification 1 of all the log-normal estimated models.

Table 10
Mean, variance, and 95% confidence intervals of the Cox-Snell residuals of the preferred models A1 to A4: All firms (from Table 5).

Preferred Model	Mean (95% confidence interval)	Variance (95% confidence interval)
Model A1	1.221 (1.092; 1.351)	0.878 (0.800; 0.961)
Model A2	1.216 (1.089; 1.341)	0.857 (0.781; 0.939)
Model A3	1.226 (1.098; 1.354)	0.865 (0.788; 0.950)
Model A4	1.221 (1.092; 1.351)	0.876 (0.799; 0.960)

Note: If the Cox-Snell residuals follow a unitary extreme value distribution, both their mean and variance must be statistically equal to 1.

whether the Cox-Snell residuals follow a distribution of unitary extreme value, that is, with mean and variance equal to one. As shown in Table 10, this condition is fulfilled for the models we have estimated, so their validity is statistically confirmed. For reasons of simplicity, we have only displayed the information on the models relative to all the firms (A1–A4), but similar results have been achieved for the rest of the models. That is, the Cox-Snell residuals of all of them follow a distribution of unitary extreme value, hence they all are adequate.

6. Conclusions

Using a prosopographical approach, we have collected data on the longevity −years from entry to end of the original entrepreneurial project– and innovation activity −measured by significant innovations (SI) and by total patent applications– of two hundred top British firms active throughout the nineteenth and twentieth centuries. We have tested the relation between innovation (and its types) and business survival, controlling for five features of the companies and seven of their business leaders. We have done this for the overall set of firms and for the manufacturing and service ones separately to control for industry differences. In addition, for robustness check, we have developed the same analysis dividing the sample by periods of entry. For the econometric test, we have used a parametric duration model, which implies the assumption of a specific density function for the dependent variable. Among the possible options, we have found that the two most adequate − from the statistical point of view and the characteristics of the endogenous variable– are the log-normal and the gamma distributions, both of them having provided very similar results.

Respecting the main focus of the study − the relation between innovation and business survival–, the conclusions can be summarized as follows. When we look at the whole group of firms, the SI show a positive and significant influence on the probability of business survival, while the overall number of patents does not seem to have any effect. This would indicate that the longevity of the top British companies has depended more on a few significant (radical) innovations than on many incremental ones. But not all SI are the same: when they are disaggregated by types, new process, non-patented and domestic innovations emerge as the specific ones influencing survival. But when the set of companies is divided by industries, the results are quite different. In particular, the manufacturing firms' survival is influenced positively and significantly by their total patent applications and not by their SI, except when the latter refer to new processes. Thus, incremental innovations seem to be more important than radical ones for the manufacturing firms' longevity, although the positive effect of new processes reinforces the relevance of this specific type of SI. On the contrary, business survival in services is positively and significantly affected by SI (new products and new processes), but not by total patents, which in part can be explained by the fact that patents are mostly oriented towards manufacturing. When the sample is divided by period of entry, both the companies that entered before and after 1875 show a positive relation between innovation and survival. This is a sign of robustness of our estimations and suggests the unlikelihood of an endogeneity problem, namely, that the earlier firms had an advantage to innovate compared to the most recent ones. Although the types of innovation influencing survival differ between the firms entering during the 'golden age' of the British economy (1816–1875) and those entering later on (1876–1957), this is reasonable and coherent with our previous findings.

In relation with the five firm-level control variables included in the analysis, the size achieved by the firm appears to be the most important one, as it affects positively and significantly the probability of business survival of the whole set of companies as well as of all the sub-groups separately (manufacturing and service firms, and those entering before and after 1875). Having branches abroad (being a multinational) influences positively and significantly the probability of survival of the whole set of firms and of those entering in the first and the second period, as well as of the services group, but not of the manufacturing one. The same happens with the family business tradition, with the exception of the firms entering in 1816–75, for which this factor is not influential. Having an outstanding CSR seems to increase the survival probability only of the manufacturing firms. The only factor reducing the probability of survival is the exporting activity, but only for the services group and the firms entering before 1875.

Lastly, among the seven business leader's personal traits included as control variables, the most influential is the age at founding (or entry) as it is significant in all the estimations except for the group of firms entering in 1816–75. The negative sign of the coefficient in all the cases indicates a non-linear effect of age (taken in logarithms) on the firm's longevity. Two other traits − previous experience in the same sector and being of a high social background– show a significant (and positive) effect on survival, but only for the service firms, thus indicating that the personal influence of the business leader is particularly relevant in services. Being an inventor seems to affect (negatively) the survival probability only of the firms entering after 1876. The business leader being the founder as well as his educational characteristics − having college studies or an apprenticeship– do not show any influence on the survival probability of the top British firms. A more detailed analysis of these features, such as differentiating by types of higher education, would maybe provide a more nuanced result, this being an interesting field for further research.

The aforementioned results show the usefulness of the prosopographical approach to provide new empirical evidence about the complex nature and effects of innovation on business survival. They apply to the business elite of a specific country. So an interesting task for the future would be to construct similar databases for other countries in order to find out to what extent the patterns found here can generalize. In terms of policy implications, the study suggests that developing significant innovations − particularly new processes– would be the most effective way to increase the probability of business survival in general. But the innovation strategies should differ by sectors, the promotion of continuous incremental innovations being more important in manufacturing, while service firms would rather opt for fewer but more relevant innovations, both in products and processes. Finally, educational programs to stimulate innovative startups among young people would probably increase the number of long-lasting and large employment providing companies.

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Appendix A, B and C. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.respol.2018.04.019.

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