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(*) The opinions and analyses herein are the responsibility of the authors and, therefore, do not necessarily coincide with those of the Banco de España.

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Abstract

The impact of entry upon market performance depends not only on the number of entries and their size, but also on how long do the firms last. Consequently, there are an increasing number of papers, most of them focused on the United States and restricted to the manufacturing sector, aimed at analysing the post-entry performance of firms. Unfortunately, there is not much about this important topic in Spain due to the lack of appropriate longitudinal micro data on firms. The current paper aims to fill this gap by means of a new database covering all sectors of the business economy constructed at the Bank of Spain. We study the determinants of new firm survival using non-parametric and parametric procedures especially designed to analyse duration phenomena. We find that larger start-ups survive longer and that the probability of exit is larger in sectors with high entry rates and low concentration. One of the contributions of the paper is the inclusion of the initial firm's financial structure among the determinants of survival. Our results suggest that holding debt, instead of equity, has positive and important effects on survival up to some point. Beyond this point, further debt increments have a negative impact on survival, and this effect is more important the higher is the corresponding debt ratio or indebtness of the firm.

JEL classification: L11, L25, G33, M13.

Keywords: Firm survival, entry and exit, micro-data.

1 Introduction

At the beginning of the last century Joseph Schumpeter wrote the *Theory of Economic Development* and *Capitalism, Socialism and Democracy*, two ground breaking studies where he introduced the concept of creative destruction as the force behind economic growth. Although quite challenging at the time, the idea that the creation of new businesses and the decline of unproductive ones is key to the overall dynamism of the economy is now widely accepted thanks to the mounting evidence on the issue [see Scarpetta et al. (2000)]. Indeed, a recent OECD analysis of the contribution of entry and exit as well as incumbents' expansion and contraction to the aggregate productivity growth has found that firm demography can explain between 20 and 30% of productivity growth [Foster, Haltinwager and Krizan (1998)]. Apart from reallocating resources from low to high productivity units, firm entry and exit is thought to have as well an indirect impact on productivity by increasing the competitive pressure on incumbent and new firms to innovate and increase their efficiency.

A recent cross-country OECD study[1] [Bartelsman, Scarpetta and Schivardi (2003)] has established that a large proportion of firms in a given market –around 20%– are either recent entrants or will close down within the year. However, the process of entry and exit of firms involves proportionally low number of workers since entrants are generally smaller than incumbents. This could lead to the conclusion that entry and exit of firms do not play an important role in the job generation process. But that conclusion could be wrong. As it was established by David Birch back in the 1980s, "Not all small businesses are job creators. The job creators are the relatively few younger ones that start-up and expand rapidly in their youth, outgrowing the "small" designation in the process [Birch (1981), page 8]". According to the few studies on the topic, as little as 3-5% of any given cohort of new firms may end up creating up to 80% of all new jobs [Birch et al. (1997); Davidsson et al. (1994); Kirchhoff (1994); Storey (1994)].

Given the sizable potential impact of firm churning and firms' post-entry performance on productivity growth and job creation, it seems quite important to improve our understanding of the determinants of firm entry, survival and growth. There has been a quite recent surge of analyses on the post-entry performance of firms started by Troske (1989) and Audretsch and Mahmood (1994), both focusing in the United States. Troske established in his paper that firm failure decreased with firm size and Audretsch and Mahmood (1994 and 1995) found that firms lasted longer in fast growing industries and in those where innovation and R&D are less important. Audretsch (1991) studied the survival rates of firms as a function of industry-specific variables such as innovation, economies of scale or concentration, finding that although entry is large, survival is small in high-technology industries with large economies of scale. Market concentration was found to promote short-term (one or two year) survival but had no effect on the long-run one (more than five years). Mata and Portugal (1994) studied for a sample of Portuguese firms the effect upon survival of ownership and industry turbulence and growth, while Mata, Portugal and Guimaraes (1995) and Geroski, Mata and Portugal (2003) analysed the importance of strategic choices and environmental conditions at entry time, as opposed to those at current time.

1. The OECD study covers the following countries: USA, Germany, France, Italy, United Kingdom, Canada, Denmark, Finland, the Netherlands and Portugal.

Most of the studies refer to the United States, with the important exception of the extensive research performed by Mata, Portugal et al. on Portuguese firms [see for example Mata, Portugal and Guimaraes (1995)], and are limited to the manufacturing sector. Very few studies are available at the international level in order to allow for an analysis of the role of institutional settings for firm dynamics. The reason of this scarcity lies mostly on measurement problems due to differences in sector coverage, different criteria to include firms in the study (very often only the firms with one or more employees or with a turnover above a certain threshold are included) or differences in the unit of study (establishment versus firm). The OECD and Eurostat are currently doing an effort to harmonise firm demographic data on a number of countries[2].

In Spain there is still a lot to be done, and learnt, in the field of firm dynamics. The few analyses available to date refer to the manufacturing sector, see for example Fariñas and Ruano (2004 and 2005) and Martín and Jaumandreu (1998), who using the "Encuesta sobre Estrategias Empresariales"[3] estimate the contribution of firm churning (entry and exit) to the overall productivity growth in the manufacturing sector. To our knowledge, the only study covering firm entry and exit, as well as post-entry performance, of firms in all economic sectors in Spain is produced by Eurostat, via its periodical publication "Business Demography in Europe"[4]. However the Eurostat study does not have any firm-specific information other than the turnover, employment and broad economic sector in which the firm operates. Therefore the analysis cannot explain properly the time period between firm birth and its disappearance from economic activity, which is crucial for policy-making.

The current paper attempts to fill this gap using a new longitudinal database with around 90,000 Spanish firms born between 1995 and 2002 across all sectors in the business economy. The data set contains information about the moment of entry and exit of firms, 4-digit economic sector of activity, legal form of the firm and the start-up size (number of employees at birth). We have access as well to some detailed financial data taken from the firms' accounts. The richness of this data set allows conducting a comprehensive analysis of firm dynamics in Spain, covering the determinants of firm survival as well as the contribution of firm churning and growth to productivity and employment. As a first step, this paper focuses exclusively on firm survival and its determinants in Spain using non-parametric and parametric procedures especially designed to analyse duration phenomena. Apart from being the first analysis able to study the post-entry performance of Spanish firms in all sectors of the business economy, the paper makes a contribution to the firm duration literature by studying the impact of the initial financing decisions upon firm's survival, after controlling by the usual firm and industry-specific variables.

The next section describes the data set in detail. Section 3 collects the stylised facts established in the literature on firm entry and exit and tests whether they also hold in Spain according to our new data set. Section 4 performs a non-parametric analysis whereby the survival function and hazard rate of firms in different economic sectors and with different start-up sizes are studied. Section 5 resorts to parametric analysis to study the determinants of firm survival. Finally, section 6 concludes.

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2. See Bartelsman, Scarpetta and Schivardi (2003).

3. The "Encuesta sobre Estrategias Empresariales" is an annual survey of Spanish manufacturing firms sponsored by the Ministry of Industry, which is carried out since 1990.

4. See European Comission (2004).

2 Description of the data set

Our data set (called hereafter the Bank of Spain Firm Demography Database or BSFDD) consists of a sample of around 90,000 firms born between 1995 and 2002 across all business economic sectors[5]. The database has been constructed from two main sources of information. The first one is the firm registries. All companies in Spain are required by law to deposit annually their accounts in the registries. In spite of that, there are numerous gaps in the information provided by the registries which makes it difficult to deduct the date of entry and exit of firms solely from this source. For that reason we resorted to a second source of information, namely, the Spanish Central Directory of Firms (DIRCE)[6], to establish the duration patterns of a sample of firms for which other micro information was available from the registries. For further information about the construction of the dataset, please refer to the annex.

The subject of analysis is the firm, as opposed to plants or establishments. In other words, a firm with several active plants is considered as only one observation. It is important to clarify from the outset that we do not have information on self-employed workers; all observations in the data set correspond to Limited Liability societies or Corporations. The reason is that the latter are identified with a fiscal identity number, which is firm-specific, that makes it easy to follow them along time. Self-employed workers, on the other hand, use the personal identification number for fiscal purposes making therefore very difficult to know whether they are active or not in a market. These two features (firm approach and exclusion of self employed) should be kept in mind while interpreting the results in the following sections.

Each firm has associated a variable which records each year whether the firm is new, continues its previous activity, or disappears in the given period. With respect to the economic information, we have data on the number of employees of the firm each year and on the economic sector (at a 4-digit detail) in which the firm carries out its main activity. Additionally, we have access to the annual financial statements deposited in the registries by each firm, which include the balance sheet and the income and expenditures account.

Due to the fact that many firms do not report some of those economic variables for one or more years within their life time-span, we have restricted the sample to firms with complete data in terms of the variables that will be used in this paper, namely, sector, start-up size and initial financial structure[7]. The sample of firms with complete data is representative of the total population, at least in terms of sector of activity, legal form and employment. In order to see that, we compare the distribution across sectors and legal forms of the total population of active firms in 1999 constituted as Corporations or Limited Liability in the business economy provided by the DIRCE[8] with that in our sample. Table 1 below shows the result of the exercise. The comparison is done for a single year, in this case 1999, but results do not change if another year was chosen instead.

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5. That is, excluding agriculture and fishing and social and community services.

6. DIRCE is run by the Spanish National Statistics Institute. For a detailed description of the DIRCE data please refer to the Spanish National Statistics Institute's web page. www.ine.es.

7. We were not able to distinguish between firms which chose not report employment data and those with zero employees. Hence we opted to restrict also the sample to start-ups with one or more employees.

8. Entries were restricted to have one or more employees whereas continuing firms were of all sizes in order to mimic as much as possible our sample.

Table 1: Distribution of firms across sectors of activity and legal form in 1999: Population versus BSFDD (figures in percentage of total)

Sector[9]	**DIRCE**	**BSFDD**
Primary sector	0,90	0,37
Manufacturing	17,85	20,13
Utilities	0,21	0,29
Construction	15,96	16,42
Hotels & Restaurants, Trade	37,96	35,51
Transport, Storage & Communications	5,76	5,65
Finance, Insurance, Real State an B2B	21,36	21,64
Legal Form	**DIRCE**	**BSFDD**
Corporations	20,08	10,88
Limited Liability Firms	79,92	89,12

Please recall that the BSFDD comprises firms born between 1995 and 2002. Hence active firms in 1999 are at most 4 year-old. Of course this is not the case for the total population of active firms in 1999[10]. In spite of that difference, if one considers the sector of activity to be quite stable along a firm's life, comparisons as the one shown in Table 1 are approximately correct. However, the difference in average age of firms could be behind the slight over-representation of Limited Liability firms in the BSFDD since firms tend to start as Limited Liability companies and eventually, after some years, change to Corporations.

To show that the BSFDD is also a representative sample with respect to firm size is not as easy as it is with respect to legal form and sector. The reason is that firm size does change along a firm's life and therefore we cannot compare the size distribution of our sample of quite young firms with that of the population. We have opted to compare the size distribution of firms entering the market in 1999 (with one or more employees). The result is shown in Table 2.

9. The primary sector (including extraction of raw materials) includes sector 10 to 14 NACE-93; construction includes sector 45 NACE-93; Manufacturing includes sectors 15 to 37 NACE-93; Utilities include the production and distribution of gas, electricity and water which are sectors 40 and 41 NACE-93; Transport and Communication (land, sea and air transport, including all related activities like travel agencies and post and communications) include sectors 60 to 64 NACE-93; Financial services, real state services, insurance and business to business services are sectors 65 to 74 NACE-93; and retail and whole trade, hotels and restaurants include sectors 50 to 55 NACE-93.

10. The aggregate data published by DIRCE does not provide any firm-specific information. Hence we do not know the age of the firms with which we compare our sample. That is the reason why we could not restrict the population sample to 4 year-old firms at most, which would have resulted in two entirely comparable samples.

Table 2: Start-up size distribution in 1999: Population versus BSFDD (figures in percentage of total)

Start-up size	DIRCE	BSFDD
1-5 employees	81,33	73,16
6-9 employees	9,03	12,52
10-19 employees	6,02	8,49
20+	3,63	5,83

In spite of the fact that start-ups in our sample are slightly larger than those in the population, we consider the BSFDD to be representative also in this respect.

Another check of the goodness of the data is to compare entry and exit rates computed from the BSFDD with the aggregate data published by DIRCE. We also compare the entry and exit rates from the BSFDD with those from the "Encuesta sobre Estrategias Empresariales"[11]. To be able to compare entry and exit rates computed from the total population of firms to those computed from the BSFDD we select comparable groups of firms from both sources. That means selecting on the one hand corporations and limited liability firms operating in the business economy from the population and, on the other hand, a sample of firms not only born but active in any moment between 1995 and 2003 which will be called "extended BSFDD". Entry and exit rates are computed as entries and exits in a given year as a percentage of total active firms at the end of that year (that is, entries plus continuing firms) respectively. The comparison with the "Encuesta sobre Estrategia Empresariales" (ESEE) is done using only our sample of manufacturing firms.

What we find is that both entry and exit rates are systematically lower in our sample. The only exception is the higher entry of large firms in our sample when compared to the "Encuesta sobre Estrategia Empresariales". This divergence can be due to the fact that the Encuesta is able to distinguish between real entries and mergers and acquisitions as well as spin-offs and such whereas we interpret all of those phenomena as (large) firm entries.

The generally lower entry and exit rates in the BSFDD observed in Table 3 cannot be due to differences in the representation of certain sectors or legal forms in our sample because they can be found at a more disaggregated level. Most likely, the difference responds to the fact that firms going through difficulties choose not (or forget) to deposit their accounts in the firm registries. The fact that our sample of firms includes only firms which have deposited any data in the registries during the period of analysis could result in an under-representation of firms going through difficulties and, therefore, firms most likely to exit; hence the lower computed exit rates. Although this possible bias should be taken into account while interpreting the results, especially at an absolute level, we expect that the relative results will not be affected in a substantial way. By relative results we mean, for example, the effect of the explanatory variables on the hazard ratio. That effect depends

11. We compare the rates for small and large firms separately. Please note that entry rates in the ESEE are not entirely representative of entry into the manufacturing sector.

on the characteristics of firms exiting the market at a given time in our sample when compared to the characteristics of firms staying, not on the absolute number of firms exiting. Moreover, the fact that we count with a large number of firms in our sample ensures that those relative results are quite reliable.

Table 3: Comparison of entry and exit rates of our sample to the aggregated data published by DIRCE and to the "Encuesta sobre Estrategias Empresariales" (ESEE), 1999

Legal Form	Sector	Entry Rate			Exit Rate		
		BSFDD	DIRCE	ESEE	BSFDD	DIRCE	ESEE
Corporations	Industry	2.2	2.3		2.1	4.9	
	Services	4.1	5.3		3.6	5.9	
Limited Liability	Industry	8.9	11.9		2.0	6.7	
	Services	12.7	17.1		2.6	7.5	
All	Business Economy	10.0	12.2		2.9	7.2	
	Industry	7.1	9.4		2.0	6.2	
	Services	10.9	14.8		2.8	7.2	
	Manufacturing						
	<200 empl.	6.8		9.7	1.2		3.0
	>200 empl.	2.8		0.4	0.6		0.4

3 Firm entry and exit: Some stylised facts

There are some theoretical models able to give a formal explanation to Schumpeter's creative destruction process. The best known are those related to the process of learning of firms. Jovanovic (1982) describes a process of *passive* learning whereby new firms do not know their potential profitability upon entry but learn about it over time thanks to the information provided by realised profits. Given the uncertainty and to minimise risks, firms enter the market small and then decide to expand, contract or exit, depending on the new information about their own profitability. By contrast, according to Ericson and Pakes (1995) firms are *active* in the process of learning about their environment and invest to foster their productivity. Returns from investment are stochastic and determine the success of the firm and therefore its expansion, contraction or exit.

Another type of models able to explain the coexistence of very different firms –with respect to age, size, technology and so forth– in the market implied by Schumpeter's theory of creative destruction are the vintage models of technological change [see Mortensen and Pissarides (1994)]. These models assume that new technology is embodied in the new capital vintage. The user cost of such capital includes the cost of reorganising production which is naturally lower in new firms. This highlights the importance of new firms for new technology adoption. Although obsolete firms are eventually kicked out of the market, some survive due to the sometimes large sunk costs they had to face.

The empirical literature on firm demographics has found a number of common trends, or stylised facts, across countries and periods of analysis which are coherent with the predictions of the theoretical papers. In this section we review those stylised facts and study whether they hold in Spain, according to our data. When possible we will resort to data from other countries in order to compare them to the Spanish results[12]. Please keep in mind several caveats of our data set which, on the other hand, are common across empirical studies of this kind. The first caveat relates to the inability to distinguish between real firm births and deaths and those resulting from merges and acquisitions, spin-offs or such. The fact that several firms in our data set start off with more than 500 employees yields us to suspect that we might have some of those "false" firm entries in the BSFDD. Secondly, as it was shown in the previous section, computed exit rates from the BSFDD are a bit lower than the ones calculated by the Spanish National Statistics Institute using the whole population of firms (of the same characteristics in terms of legal form and sector), and this is something consistent across years.

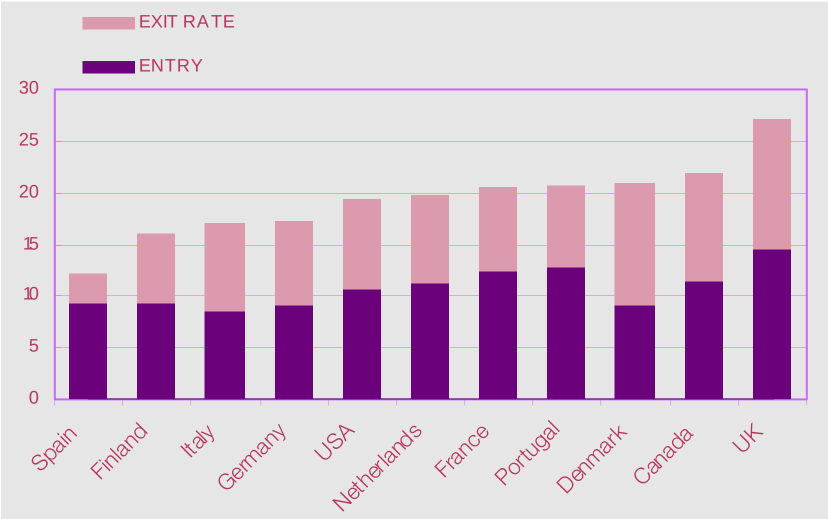
3.1 Stylised facts from firm dynamics

There are a high number of firms that enter and exit a given market every year. The OECD has estimated that between 15 and 20 percent of active firms in a given year enter the market or exit during the course of the year. That is, around a fifth of firms in a given year in a given market are either being created or destroyed. Figure 1 shows the entry and exit rates for a number of OECD countries along with the rates calculated for Spain using the extended BSFDD. The entry rate is defined as the number of firms that enter into a market in a given year as a percentage of all firms active at the end of the year in that market (that includes the new and continuing firms). The exit rate is the number of firms exiting the market in a given

12. Data from other countries come from the OECD database on firm demographics. Aggregate data on entry and exit for several OECD countries can be found online at www.oecd.org.

year as a percentage of the active firms in that market at the end of that year. Lastly, the turnover rate is a measure of firm churning and is defined as the sum of the entry and the exit rates, that is, it is the percentage of active firms that either enter or exit a market in a given year. The figure shows average rates calculated over different periods of time (mostly early 90s)[13]. They all refer to the business economy.

Figure 1: Turnover rates, OECD countries



SOURCE: OECD Firm Demography database extended BSFDD.

a. Spain: 1996-2000; Finland: 1990-1997; Italy: 1987-1993; Germany: 1990-1998; USA: 1989-1996; Netherlands: 1990-1997; France: 1990-1996; Portugal: 1990-1997; Denmark: 1990- 1994; Canada: 1990-1997; UK: 1990-1997.

As it can be observed in Figure 1, according to the BSFDD entry rates in Spain are in line with those in other OECD countries and even exceed those encountered in Finland, Italy, Germany or Denmark. The difference lies on the exit rates, clearly below the other countries. Using the aggregate information published by DIRCE, Núñez (2004) also finds that exit rates in Spain are well below those in other OECD countries. Hence, the low Spanish exit rates graphed in Figure 1 are not only the result of the possible bias of our data set but rather responds to some other reason. As Núñez suggests, that reason could be high exit costs, which includes, for example, high firing costs. Given the existing evidence on the importance of entry and exit for productivity growth, those abnormally low exit rates could maybe explain partially the poor productivity performance of Spain over the last years. Hence the question of why exit rates in Spain are so low deserves further research.

The same pattern of entry and exit rates can be seen across different years in Spain, as Figure 2 shows. The fall of entry rates, and rise in exit rates, over the first years of the 2000 corresponds nicely to the fall in economic activity due to the crisis originated with the dotcom crash, at the beginning of the century.

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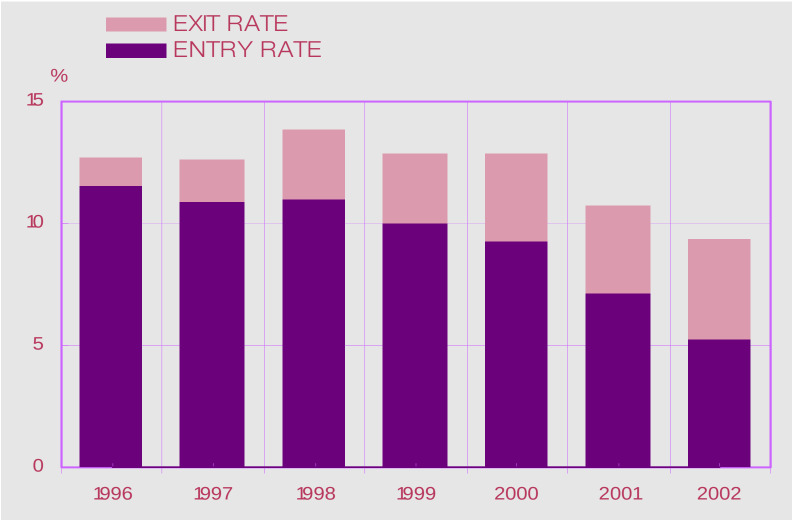
13. Please note that the fact that each country's data refer to a different period could explain part of the differences across countries shown in Figure 1. Unfortunately, these are the only firm demography data available across countries with minimum guarantees for comparability.

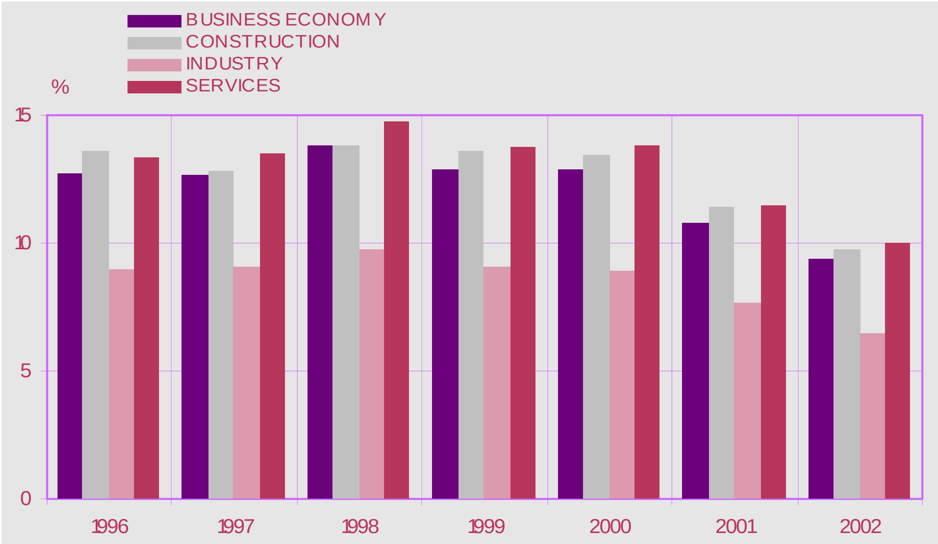
Figure 2: Entry and Exit rates in Spain, 1996 to 2002



SOURCE: Extended BSFDD.

Turnover rates are higher in the service sector than in manufacturing. Figure 3 shows turnover rates over different years for the business economy, construction, industry and business service sector. As it can be observed, turnover rates are indeed higher in the service sector than in the industry one. We have depicted the construction sector separately given its importance in terms of contribution to GDP in the Spanish economy and found that turnover rates in construction are similar to those in the business service sector.

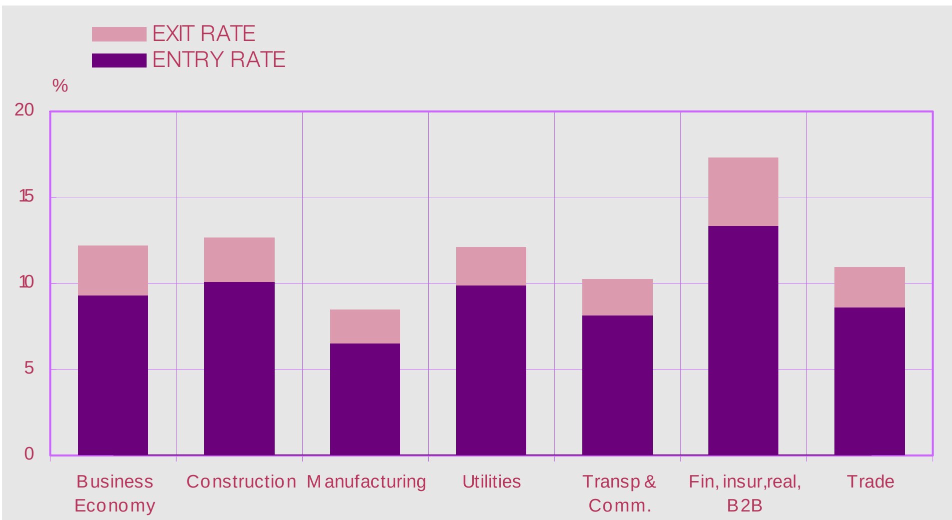
Figure 3: Turnover rates by broad economic sectors and year



SOURCE: Extended BSFDD.

In order to explore a bit further the differences in entry and exit rates across economic sectors, we have divided the broad sectors shown in Figure 3 further into their main sub-sectors. Figure 4 shows the annual average entry and exit rates for the period 1996-2002 in seven economic sub-sectors: the primary sector (including extraction of raw materials: 10 to 14 NACE-93 sectors); construction (45 NACE-93 sector); Manufacturing (15 to 37 NACE-93 sectors); Utilities (this includes the production and distribution of gas, electricity and water: 40 and 41 NACE-93 sectors); Transport and Communication (land, sea and air transport, including all related activities like travel agencies and post and communications: 60 to 64 NACE-93 sectors); Financial services, real state services, insurance and business to business services (65 to 74 NACE-93 sectors); and retail and whole trade, hotels and restaurants (50 to 55 NACE-93 sectors).

Figure 4: Entry and exit rates by sub-sectors, annual average 1996-2002

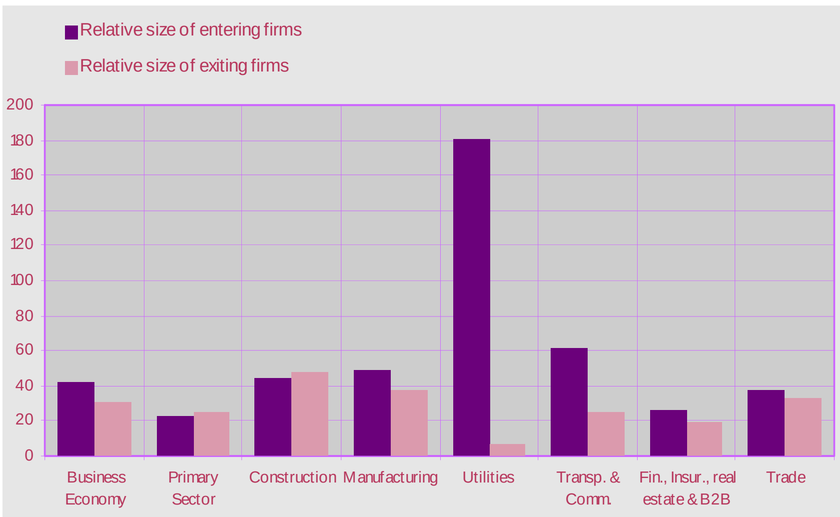


SOURCE: Extended BSFDD.

Figure 4 shows how entry and exit rates vary widely within the industry and service sector. It is interesting to note that within the service sector, the financial, insurance, real state and business to business sub-sectors show turnover rates similar to those in other OECD countries due to the high entry, but also high exit rates.

Turnover is highest among small firms. This is a direct implication of the learning models mentioned above. Firms are uncertain about their profitability and learn about it only upon entrance into the market. Therefore they prefer to enter small in order to incur in minimum costs in case of exit. To check whether this is the case in Spain, we have plotted the relative size of entering and exiting firms with respect to that of incumbents. As Figure 5 shows for the year 2000, in all sectors the average size of entering and exiting is much lower than the average size of incumbents (around a third), with the exception of new firms in the utility sector, where we have very few observations for that particular year, so the results could be distorted. The primary sector and financial et al. sector have particularly small entering and exiting firms, when compared to the incumbents. On the other hand, new firms in the manufacturing and the construction sector enter, and exit, with an average size closer to the average size of the incumbents.

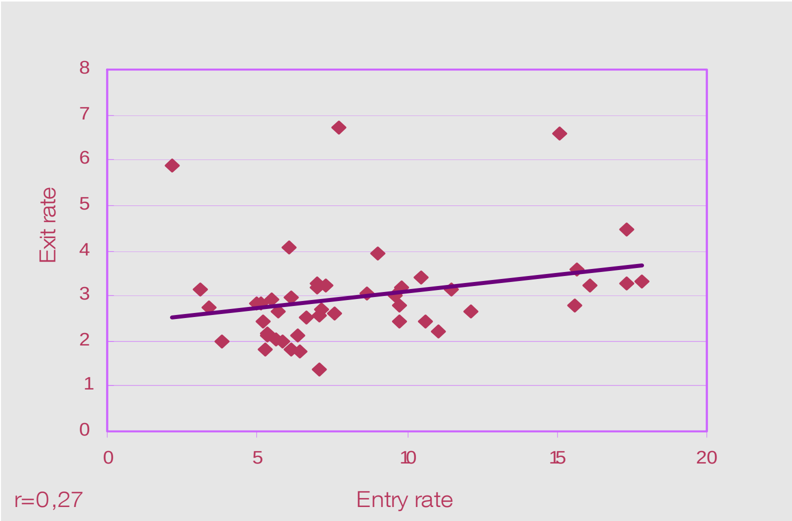
Figure 5: Average size of entering and exiting firms to average size of incumbents, in percentage (2000)



SOURCE: BSFDD.

Entry and exit rates are positively correlated. This is a very robust fact. It rejects the classical theory of firm entry and exit whereby firms enter a market when economic profits are positive and exit when profits are negative. If that was true we would expect to see a *negative* correlation between entry and exit rates across sectors.

Figure 6: Entry versus exit rates by 2-digit sectors, 2000



SOURCE: OECD Firm Demography database and BSFDD.

We have plotted in Figure 6 above the entry and exit rates across 2-digit CNAE sectors in 2000 (results do not change if another year instead was chosen). The positive relation is statistically significant and lends some support to the creative destruction process whereby the entry of new firms displaces outdated firms from the market.

4 Non-parametric analysis of survival

The positive correlation observed in the last figure between entry and exit rates across industries may be the result of new firms displacing old obsolete units; a creative destruction process. But it also could be the result of high failure rates amongst newcomers in the first years of activity. Whether this is the case can be assessed by looking at survival and hazard rates, which is what we do in this section.

We start off using non-parametric methods such as the Kaplan-Meier's to estimate the probability of survival past a certain point in time and to compare the survival experiences across different economic sectors and start-up sizes. Later on, in the next section, we will estimate the effect on survival of variables we think might have an impact.

4.1 A bit of theory: survival and hazard functions

Denote by *T* a non-negative random variable representing the time taken by a firm to exit from the moment of entry into the market or its age. The survival function is then defined as

$$S(t) = 1 - F(t) = \text{Prob}(T > t) \tag{1}$$

That is, the survivor function is the probability of surviving beyond age *t*. The survival function is a monotone non-increasing function of time: at $t = 0 \rightarrow S(t) = 1$ and at $t = \infty \rightarrow S(t) = 0$. The most commonly used non-parametric estimate of the survival function is the Kaplan-Meier estimator, which is defined as:

$$\overline{S}(t) = \prod_{j/t_j \leq t} \frac{n_j - d_j}{n_j} \tag{2}$$

where n_j is the number of subjects at risk at t_j and d_j is the number of failures. The product is over all observed failure ages less than or equal to *t*.

There is a one-to-one relationship between the probability of survival past a certain time and the amount of risk accumulated up to that time. The hazard rate measures the rate at which the risk is being accumulated. More concretely, the hazard function *h(t)* is the instantaneous rate of failure conditional upon the subject having survived to the beginning of that instant:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr ob(t + \Delta t > T > t) / T > t}{\Delta t} = \frac{f(t)}{S(t)} \tag{3}$$

where $f(t) = \frac{dF(t)}{dt}$

Therefore, the cumulative hazard function can now be defined as the integral over the period (0,*t*) of the instantaneous hazard rates:

$$H(t) = \int_0^t h(u)du = \int_0^t \frac{f(u)}{S(u)}du = -\int_0^t \frac{S'(u)}{S(u)}du = -\ln S(t) \qquad (4)$$

The most common estimator of the cumulative hazard is the Nelson-Aalen estimator which is simply defined as

$\overline{H}(t) = \sum_{j/t_j \le t} \frac{d_j}{n_j}$, that is, it is the sum of the instantaneous ratio of the failures to the number of subjects at risk.

After this brief introduction to the main concepts we will be using in this section, we proceed to depict the survival function for the firms in our data set by economic sector and by start-up size. We will finish this section with the plot of the unconditional hazard function.

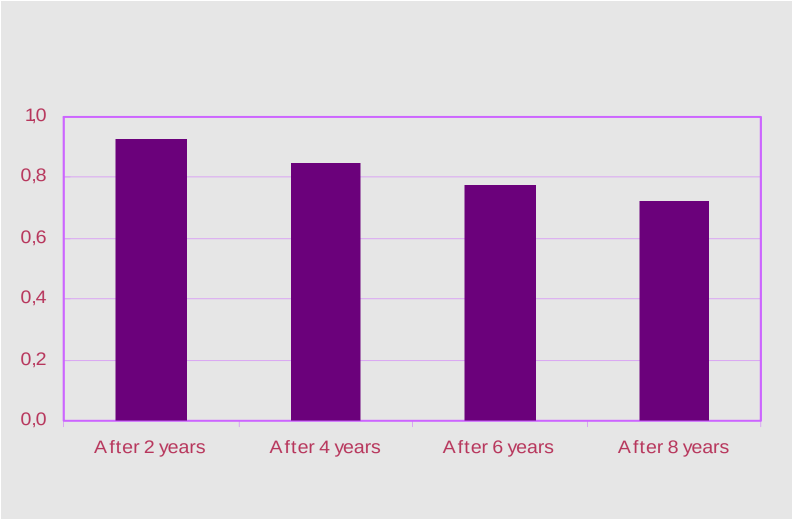
4.2 Survival and hazard functions

The OECD estimates that about 80 to 60 per cent of entering firms survive beyond the first two years of operations (that is, between 20 to 40% fail within the two first years). Only about 40-50 per cent of total entering firms in a given cohort survive beyond the seventh year. According to our data, survival rates in Spain are a bit higher than those reported for other OECD countries. Figure 7 shows average survival rates for Spanish firms operating in the business economy at different lifetimes. About 90% of those entering a given year survive more than two years and about 70% are able to make it pass 8 years. The Eurostat study[14] "Business demography in Europe" estimates two-year survival rates for Spain to be about 80%, that is, below the one found in the current paper but still larger than in other countries[15]. The finding that firms in Spain enjoy higher survival rates than those in other countries is coherent with the lower exit rates reported earlier in the paper.

14. See European Comission (2004).

15. Eurostat has information on self-employed workers which we do not so the data sets are not entirely comparable In any case, the absolute survival rates could also be affected by the bias described in section 2.

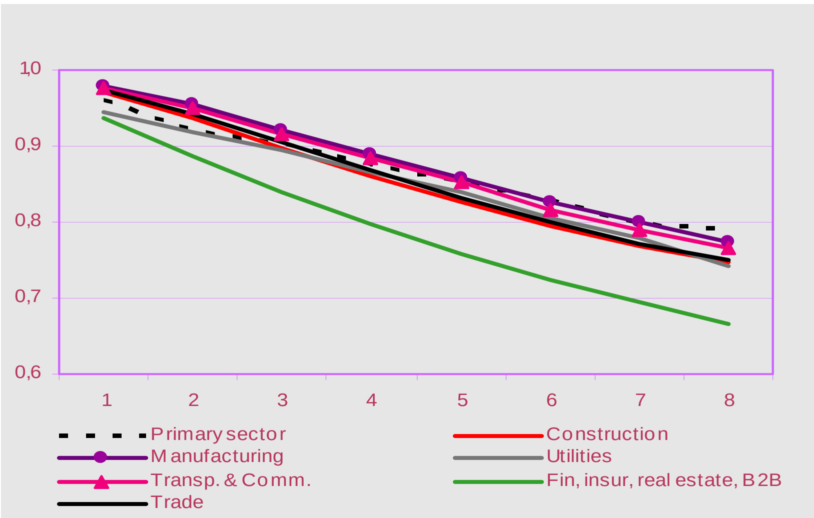
Figure 7: Average firm survival at different lifetimes, business economy



SOURCE: BSFDD.

Figure 8 shows the survival rates at different lifetimes across broad economic sectors. In a consistent way firms operating in the manufacturing sector have lower probabilities of failing than those in the remaining sectors. This is coherent with the statement made earlier about the lower dynamism, entry and exit rates, observed in the manufacturing sector when compared to the service one. As observed in the previous section, the financial, insurance, real state and business to business sectors are the only ones displaying a similar behaviour to that observed in other countries of our surrounding.

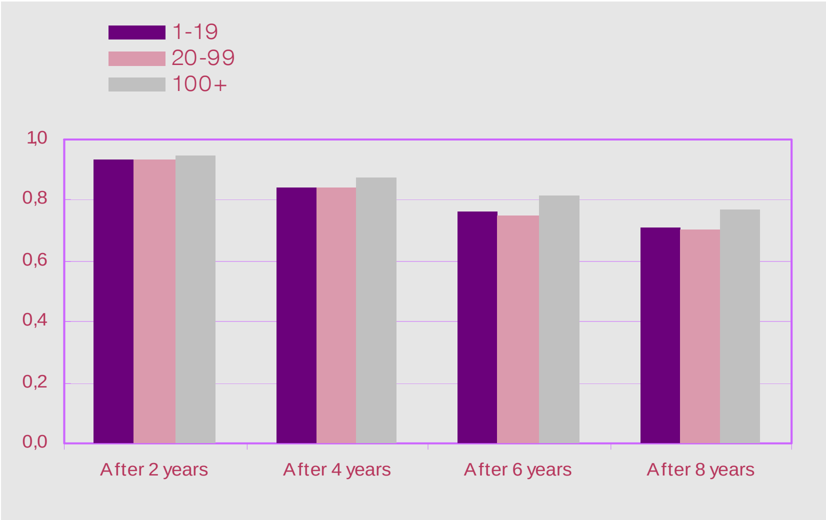
Figure 8: Survival functions, by sub-sectors



SOURCE: BSFDD.

Finally, we have depicted the survival rates at different lifetimes for firms with different start-up sizes (1 to 10 employees; 20 to 99 employees; 100 or more employees). Figure 9 shows that firms that start-up large enjoy slightly higher survival rates at all lifetimes than firms starting small, although differences are not significant.

Figure 9: Firm survival, by start-up size



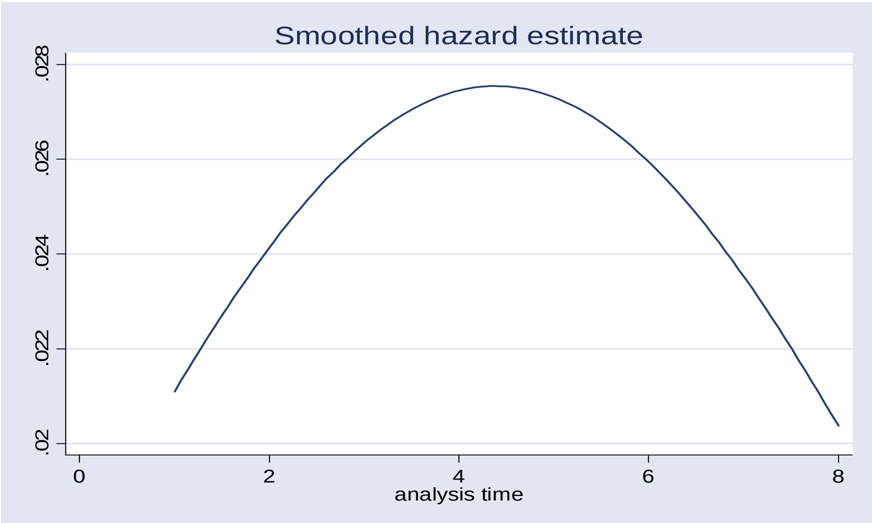
SOURCE: BSFDD.

While survival rates decline with firm age by construction, a priori there is nothing that precludes hazard rates to have other patterns of change over time. Most studies show that hazard rates tend to decline steeply with age in the first years to stabilise to fairly constant values thereafter. That is, provided that the firm has survived the first two years, for example, the probability of failure within the third year of operation is clearly below that of the previous years. This negative duration dependence is consistent with the implications of theoretical models such as Jovanovic (1982) stating that upon entrance in the market firms learn about their efficiency and if found non-profitable exit. However, some studies referring to firm survival patterns in countries such as the UK, Italy or the US have found inverted-U shaped hazard functions. For example, for the case of Italy, Audretsch, Santarelli and Vivarelli (1999) estimate an unconditional hazard function for Italian manufacturing firms that increases up to two years and decreases thereafter; in a very recent paper, Bhattacharjee (2005) estimates a conditional and unconditional hazard function for quoted UK firms that increases up to three years post-listing and then declines; Wagner (1994) finds as well an inverse-U shaped hazard function for small German manufacturing firms with a maximum around 3 years after entry. Using a different database, Bartelsman et al (2003) find also a clear inverted-U shaped hazard function for the UK, Italy and the US.

Ericson and Pakes (1998) and Bhattacharjee (2005) argue that an inverted-U shaped hazard function is consistent with the theoretical models of active and passive learning if one assumes that the new firms need some time to learn about their efficiency. This type of behaviour has become known in the literature as the “liability of the adolescence”, in opposition to the “liability of the newness” which describes the monotonically decreasing hazard rate. It was, Bruderl and Schussler (1990) on the one hand and Fichman and Levinthal (1991) on the other, the first ones in using this term. They explained this behaviour with the fact that new firms often have a stock of initial resources which help them survive for some time during which they can establish their new structures. It is the existence of those initial operations what might explain that firms take some years to learn that they are not efficient and, consequently, exit the market. This would be more so if the firm had to sustain large sunk costs to enter the market. In this case the firm will try to stay as much as its initial resources allow before giving up and leaving the market.

Spanish firms seem to show a similar behaviour to that just described. The non-parametric or unconditional hazard function, calculated for the overall business economy and shown in Figure 10, shows a clear inverse-U shape with its maximum around the fourth year of operation. That is, after entry, the conditional probability of failure increases continuously until the fourth year. Thereafter, and given that the firm has survived those first years, the hazard rate declines steeply. Later in the section a conditional (that is, controlling for other variables) hazard function will be computed for the business economy as well as for some economic sectors.

Figure 10: Hazard function, business economy



This section has taken a first look to Spanish firms' survival rates. We have found several interesting results. The first one is the higher-than-in-other-countries survival rates of Spanish firms at all lifetimes. This result is coherent with the reported low exit rates in section 3 and consistent across economic sectors and start-up sizes. The second result of some interest is related to the estimated non-parametric hazard function. We found that the hazard rate displays an inverted-U shape with a maximum around 4 years.

5 A semi-parametric analysis of survival

5.1 A bit of theory: The Cox proportional hazard model

Hazard models are written in the form: $h_j(t) = f(h_0(t), \phi(X, \beta))$ which can be read in the following way: The hazard subject j faces is some function of the hazard everybody faces (the baseline hazard h_0), modified by a set of explanatory variables *X*. The relationship between explanatory variables and survival depends on some vector of parameters ***β***. Please note that under this model, two different individuals of the same age will face a different hazard function if and only if their other characteristics or explanatory variables are different. A very popular way to parameterise the model is the following:

$$h_j(t) = h_0(t)\phi(X, \beta) \tag{5}$$

which is known as a proportional hazard model because the hazard an individual faces is multiplicatively proportional to the baseline hazard, $h_0(t)$, which is the hazard corresponding to $\phi(X, \beta)$ =1. In other words, the shape of the hazard function is the same for all individuals, and variations in the explanatory variables will translate into parallel displacements of this function, thereby affecting only the scale of the hazard function and not its shape. It is possible to re-scale the explanatory variables in such a way that the baseline hazard represents the hazard for the mean individual of the sample.

Given the fact that the hazard is a conditional probability and, therefore, must be positive, a convenient functional form for $\phi(X, \beta)$ is the exponential one. Hence the hazard a subject j faces is written in the following form:

$$h_j(t) = h_0(t)e^{X'\beta} \tag{6}$$

Note that this particular functional form offers the advantage of a very convenient interpretation of the estimated coefficients since $\beta = \frac{\partial \ln \phi(X, \beta)}{\partial X}$. In words, the coefficient of one explanatory variable is the constant proportional effect of a unit increase of this variable on the conditional probability of exiting.

A parametric estimation of the hazard above would require some assumption on the functional form of the baseline hazard. Although economic theory sometimes gives enough hints as to how the baseline hazard might vary along time, some other times we prefer not to make any assumption about the functional form and instead let the data speak. Cox (1972 and 1975) suggested a way of estimating the impact of the explanatory variables X in a proportional hazard model in which the shape of the baseline function was not known. Such models are called semi-parametric since the baseline hazard is not given any particular parametrisation. This is achieved by pooling over the risk groups based on ordered survival times. As we saw in the last section, the hazard rate of firms need not be monotonically decreasing with time. Hence we do not have a clear idea “a priori” about the shape of the function in this particular case of firm survival. Hence we will treat the baseline hazard non-parametrically by creating 8 interval specific dummy variables (one for each spell year at risk) since the longer observed spell in our data is 8 years.

In the following estimations, time is considered as a discrete variable, not because it is intrinsically discrete but because the data is provided on a yearly basis which explains that duration spell lengths are positive integers. One discrete time representation of an underlying continuous time Cox proportional hazard model as the one described above is the complementary log-log or cloglog [see Jenkins (2004)], which is the one that will be used in the estimations below[16].

We are aware of the possible existence of firm-specific unobserved characteristics, such as the quality of the project or the human capital of managers, which could have as well an impact upon firm survival. Not controlling for unobserved heterogeneity could result in inconsistent and downward biased estimates of the covariates' coefficients. However, Dolton and van der Klaauw (1995) have shown that the effects of unobserved individual heterogeneity are not so important when the baseline hazard is non-parametric, as it is in our case. In spite of that latter result, we have included one specification controlling for unobserved heterogeneity in our cloglog estimation to check for the robustness of the results once unobserved heterogeneity is taken into account. The easiest way to incorporate individual unobserved heterogeneity is including in the specification of the proportional hazard model described above a random variable following a certain distribution with unit mean (so the baseline hazard can be interpreted again as the hazard of the mean individual if explanatory variables are re-scaled conveniently) and some positive variance σ^2, as the equation below shows.

$$h_j(t) = h_0(t)e^{X'\beta}v_j \qquad (7)$$

where v_j is the value of the random variable for the individual j. The usual distribution chosen for v is that of a Gamma distribution with unit mean and positive variance, which can be estimated from the data and it is assumed to be independent of the rest of the explanatory variables X.

In summary, we will estimate a discrete time (grouped-interval data) proportional hazard model that accounts for right-censoring and unobserved individual heterogeneity, with a fully non-parametric baseline hazard. We proceed to discuss next the variables included in the model.

5.2 The determinants of firm survival

The literature on firm demography uses variables specific to the firm, to the sector or to the macroeconomic framework in which the firm operates to explain the observed heterogeneity in firms' survival. The choice of variables to be included in the analysis is determined by prior expectations based on theory and previous empirical studies.

With respect to the *characteristics specific to the firm* that might affect survival, the one the literature has found to be important is the <u>start-up size</u>[17]. Firms that start-up small survive less years than new large firms. The reasons behind this finding are varied. As it has

16. We have tried other methods to solve the problem of tied failures, with essentially the same results.

17. Mata, Portugal and Guimaraes (1995) and Geroski, Mata and Portugal (2003) argue that not only the start-up size but also the current size should be taken into account. Their argument is that after having controlled for current size, measuring initial size amounts to measuring firm performance. The fact that a firm has grown in the past signals that it has been performing well and therefore that its probability of exit is low. The problem with this argument is that current size is endogenous since firms that are about to exit shrink first and vice versa. It is true that current firm size is, as the papers above remark, a better predictor of survival time than start-up size. However, if one wants to understand the exogenous determinants of survival, start-up size seems to be a better choice.

been said somewhere else in the paper, entering small is a way of firms to avoid big losses in case experience after entry revealed that they are not efficient enough to survive. Hence new firms better informed about their success prospects start up larger. Another similar line of argument is that small firms are less capital intensive than large firms which means that variable costs represent a larger share of total costs. If there is a negative shock by which prices go down, for example, this different composition of total costs will yield small firms to exit first. Other similar arguments relate the longer survival of large start-ups with expectations: By entering large, firms are signalling the expectation of the firm-owners of a greater probability of success.

Another argument put forward to explain the low survival rate of small start-ups is that they enter small not because they choose to but because new firms are liquidity constraint. This initial underinvestment would impact negatively on firms' survival probabilities. The theoretical argument behind new firms' liquidity constraints was introduced by Stiglitz and Weiss in their 1981 seminal paper on credit rationing in financial markets with asymmetric information. Some time later, Evans and Jovanovic (1989) and Blanchflower and Oswald (1998) using a panel of individuals for whom information on employment status and wealth was available proved that the probability of an individual switching from dependent employment to self-employment was increasing with wealth, which pointed at the existence of liquidity constraints for would-be entrepreneurs. More recently, Holtz-Eakin, Joulfaian and Rosen (1994) showed that liquidity constraints are not only important for entry into entrepreneurship but are also important in explaining firms' survival since the probability of survival in their dataset increased with the size of an inheritance[18].

According to the theoretical underpinnings exposed at the beginning of section 3, survival probabilitites should be related to profitability (or efficiency) of firms. In an efficient system, firms should choose the initial assets and liability composition in such a way that profitable firms almost always survive and non-profitable firms dissapear. In this case, the initial financial stucture would be uncorrelated with survival probabilities. If, on the other hand, financial markets are imperfect or incomplete, firms with access to better financing possibilities could have higher survival probabilities. We try to check whether this is the case by including some <u>firm-specific financial variables</u> in the model. The focus should be on the financing position of the firm at the start of operations and not at the current year. The reason is that, as highlighted in footnote 17 for the case of current employment, the current financial structure of a firm could be endogenous since the probability of exit every period conditions the corresponding capital structure of the firm –either due to the firm's own choice or to the choice of its financiers–. For that reason we considered more appropriate to use the financial structure of the firm as it enters the market, that is, at birth year, to understand the exogenous determinants of survival. To our knowledge one of the few papers considering the effect of initial finance on the survival of firms is Audretsch, Houwelling and Thurik (1997) who consider the interest paid on debts divided by the number of employees as a proxy to the debt structure of the firm. They find its impact on the likelihood of survival statistically significant in the sixth year subsequent to entry and negative.

We have access to the balance sheet information of a sample of around 90,000 firms for which we also had information about their survival patterns. The balance sheet information includes total assets and liabilities and their broad components. In the liability side, we have

18. Robert Cressy (1996), on the other hand, claims that all empirical studies documenting start-ups' liquidity constrains are characterised by a common deficiency: The inclusion of only a relatively small set of human and financial capital variables in the survival function.

data on the firm's own resources and debt –short and /or long-term[19]–. As for total assets, we have some information on fixed and working capital, particularly, with respect to the latter, we have data on the firm's cash holdings. We are interested in the impact upon survival of the initial financial structure of firms: Do firms with a larger share of debt survive longer? Is the structure of such debt, in terms of long and short-term, important for the survival probability of the firms? Do firms with large cash holdings at the beginning of their life survive longer? To answer these question we have constructed three financial structure indicators: short-term debt as a percentage of total liabilities[20], long-term debt as a percentage of total liabilities and cash holdings as a percentage of total liabilities. All of them are calculated at the first year of firms' operations since we are interested in the impact of initial financial decisions on firms' survival.

Apart from firms' charateristics, such as the start-up size or the initial financial structure, the *specific conditions of the industry where entry occurs* are likely to affect business survival. Concretely, we control for two important industry features. The first one is the <u>average entry rate in the industry</u> (at 2-digit level) during the first year of operations of the firm. High entry rates could be due to the fact that the industry is starting to develop and grow. In this situation there are arguments in favour and against the survival of new entrants. On the one hand, it might be easier for new firms to survive in an expanding industry than to gain market shares from competitors that may retaliate. Furthermore, the earlier stages of development of an industry may offer new market opportunities and niches for start-ups which can help them grow fast. But on the other hand, introducing innovations embodied in new products and processes involves a great risk and, therefore, a high probability of exit.

Another important industry characteristic is the <u>degree of competition</u>, approximated by the industry concentration. Highly concentrated industries may allow suboptimal scale of new firms and therefore give some room for survival after entry [Weiss (1976)]. On the other hand, according to the Industrial Organisation literature, highly concentrated industries might as well represent a higher potential for incumbents' collusion and therefore a more aggressive behaviour towards new entries. We have tried two distinct measures of sector concentration: the Herfindahl Index and the share of the top 10% firms in terms of operating revenue in the industry total (at 2-digit level of disaggregation). The advantage of the latter over the former is that it is a relative measure whereas the former depends on the number of firms in each industry in our sample. Since firms in all sectors do not report data with the same frequency, we have chosen to use in the econometric analysis below the relative measure of concentration. To check whether it delivers reasonable results across sectors, Figure 11 shows the relative measure of concentration for the main 7 economic sectors (average across years and 2-digit sectors).

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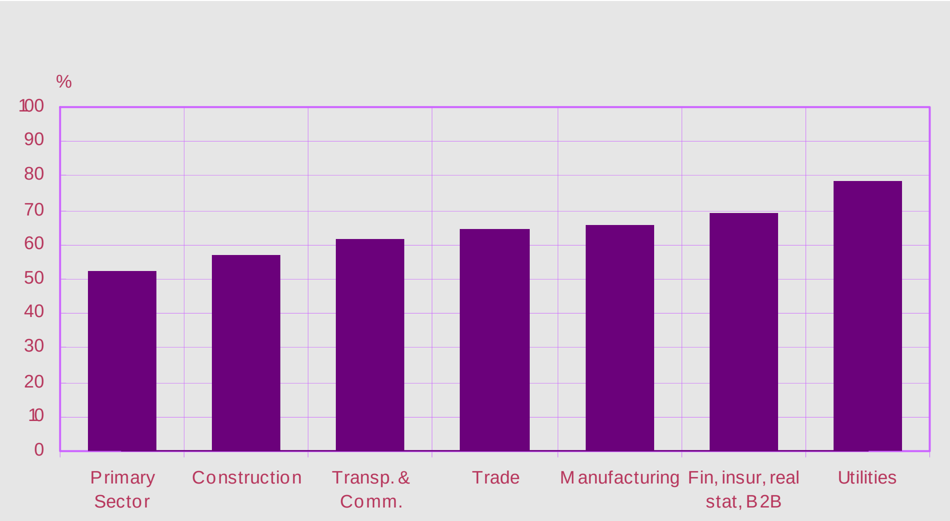
19. Short-term debt is defined as debt maturing in less than 12 months. Analogously, long-term debt refers to 12 months or more.

20. Short-term debt includes commercial credit.

Figure11: Share of top 10% firms in industry operating revenues



SOURCE: BSFDD.

The primary sector is the least concentrated sector. The relatively low concentration found in the Transport and Communication sector could be explained by the inclusion of taxis, travel agencies and moving companies (which have an index of 53%). Air and sea transport are much more concentrated, with an index of 79%. Communications, as expected, show as well one of the highest concentration indexes, with 87%. The highest concentration is found in the utilities sector, which includes the production and distribution of gas, water and electricity. The financial sector has an index of 69% but the financial auxiliary activities such as the financial markets supervision and intermediation agencies show high concentration with an index equal to 89%. Research and development and business to business activities such as consultancy, market research or portfolio management show in average quite high concentration with an index of 73%.

There may well be differences in survival rates between industries over and above those captured by the industry-specific variables mentioned above. For this reason industry dummy variables are also included in the analysis[21]. Finally, since the overall state of the economy has long been indicated as an important force driving firms out of business, we include year dummies as well to proxy the moment of the cycle.

5.3 Results

We proceed now to show the estimation results of a discrete Cox proportional hazard model whereby the explanatory variables introduced above shift the baseline hazard function. No assumptions are made about the evolution of the hazard over time. Table 4 shows the variables included in the model as well as their definition and measure.

21. Most specifications include dummies for the 7 main sectors. However, we also include a specificaton with around 50 2-digit NACE sectors.

Table 4: Explanatory variables

Variables	Definition	Measurement	Observations
Start-up size	Number of employees at birth year or the year after	Natural log of the number of employees	The literature has shown that there is a non-linear effect of the start-up size on survival which is normally accounted for via a log transformation. The specification is reasonable given that the value of the likelihood increases.
Initial short-tem debt	Less than 12 months	Percentage of short-term debt over total assets	We have considered the short-term debt at birth year or the year after
Initial long-term debt	12 months or more	Percentage of long-term debt over total assets	Same as above
Initial Cash holdings	Cash in store or in current accounts	Percentage of Cash holdings over total assets	Same as above
Industry entry rate at birth year	Calculated for industries defined at 2-digit level	Number of firms that enter in industry at birth year over entering plus incumbent firms. In percentage	
Concentration at birth year	Calculated for industries defined at 2-digit level	Operating revenue share of top 10% firms in industry. In percentage	
Dummies			Dummies for 7 main sectors (also for 50 2-digit NACE sectors) and current year

Please recall that not all firms report every variable every year. We proceeded in two ways. First, we took into account the value of the start-up size and financial conditions at the birth year, or the inmediately posterior when the former was not available. Second, we dropped all firms for which at least one of the variables was not available. After doing this we were left with a bit below 100,000 firms (for a description of the data set in terms of sector, legal form and employment, please refer to section 2).

Table 5 shows the results using different specifications of the model. The first specification includes 7 main sector dummies and assumes a linear relationship between the initial financial structure of the firm and survival, that is, it assumes that the impact on survival of a 1 percentage point increase in debt is the same independently on how indebted the firm already is. Given that the linear assumption can be a bit restrictive, we allow in specifiation (2) for a non-linear relation between debt (both short and long-term) and survival. Concretely we allow for four different debt intervals: less than 50% indebtness, between 50 and 75%, between 75 and 90%, and, finally, between 90 and 100% of total liabilities in debt. Specification (2) includes as well 7 main sector dummies. The third specifiation replicates (2) but substituting the log of the start-up size with start-up size in employees. Specification (4) replicates (2) but taking away both the sector and year dummies. Specification (5) replicates (2) but controlling for unobserved individual heterogeneity. Finally, specification (6) replicates (2) but instead of 7 main sector dummies it includes around 50 2-digit NACE dummies. Please note that due to multicollinearity problems this latter specifiation does not include the industry entry rate and concentration index since both variables are calculated at 2-digit disaggregation level.

What is shown is the hazard ratio, that is, the ratio of the hazard rate when the variable increases by one unit. A hazard ratio over one implies than an increase in the given explanatory variable increases the hazard or probability of exit and, correspondingly, a hazard ratio below one means that an increase in the variable decreases the hazard (or increases the probability of survival). T-statistics are shown in brakets.

Table 5: Estimation results

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**[a)]	**(6)**
Log of start-up size	0.8574 (-15.7)	0.8674 (-14.5)		0.8568 (-16.0)	0.7681 (-13.7)	0.8682 (-14.2)
Start-up size			0.9999 (-0.05)			
Long-term debt	0.9983 (-3.6)	0.9969 (-4.4)	0.9968 (-4.5)	0.9967 (-4.7)	0.9923 (-5.7)	0.9970 (-4.3)
Long-term debt above 50%		1.0072 (3.4)	1.0074 (3.4)	1.0071 (3.3)	1.0117 (2.8)	1.0075 (3.5)
Long-term debt above 75%		1.0033 (0.93)	1.0033 (0.91)	1.0031 (0.8)	1.0061 (0.84)	1.0036 (1.0)
Long-term debt above 90%		0.9999 (-0.01)	1.0001 (0.01)	0.9992 (-0.09)	0.9892 (-0.59)	0.9999 (-0.01)
Short-term debt	1.0001 (0.23)	0.9950 (-6.8)	0.9938 (-8.5)	0.9935 (-9.1)	0.9857 (-8.7)	0.9962 (-5.1)
Short-term debt above 50%		1.0067 (4.9)	1.0079 (5.8)	1.0079 (5.9)	1.0148 (4.2)	1.0057 (4.3)
Short-term debt above 75%		1.0061 (4.7)	1.0068 (5.2)	1.0062 (4.8)	1.0125 (4.2)	1.0057 (4.3)
Short-term debt above 90%		1.0078 (5.1)	1.0082 (5.4)	1.0078 (5.2)	1.0136 (3.2)	1.0079 (5.1)
Cash holdings	0.9992 (-1.8)	0.9991 (-1.9)	0.9994 (-1.0)	0.9992 (-1.7)	0.9975 (-2.8)	0.9994 (-1.3)
Industry entry rate	1.0182 (4.8)	1.0169 (4.5)	1.0182 (4.9)	1.0142 (6.0)	1.0456 (5.5)	
Industry Concentration	0.9955 (-3.6)	0.9957 (-3.4)	0.9953 (-3.8)	0.9998 (-0.23)	0.9924 (-3.4)	
Sector dummies	Yes (7 sectors)	Yes (7 sectors)	Yes (7 sectors)	No	Yes (7 sectors)	Yes (50 sectors)
Year dummies	Yes	Yes	Yes	No	Yes	Yes
Numer of firms	87767	87767	87767	87767	87767	87767
Log likelihood	-50815.3	-50726.1	-50836.3	-51050.7	-50648.1	-50535.2

a) Estimated controlling for unobserved heterogeneity. See note 24 for more details.

The first specification assumes that debt has a linear effect on survival, that is, one percentage point increase in short or long-term debt has the same effect on survival independently on the degree of indebtedness of the firm. Under that assumption, it seems that short term debt has no impact on survival, while an increase in long-term debt at the start of operations decreases the probability of exit of the firm. However, we should not draw any conclusions from the results of specification (1) because, according to the rest of specifications, there seems to be a non-linear relationship between debt and survival probability. Hence, (1) is clearly mis-specified. Model (2), in which the linear assumption has been relaxed and sector and year dummies have been included, is our most preferred specification, and in consequence it will be used as a benchmark. Please note that instead of assuming a certain non linear functional form, we let the data tell us how the effect of debt on survival is. To do that, we consider different intervals of indebtedness and estimate a different effect of debt in each of them. Since the estimation with five or more intervals turned out to have low accuracy we decided to consider only four intervals. Finally, we chose to make the partition finer in higher levels of debt to better capture the differentiated effects that could arise at those levels.

According to model (2), the start-up size of the firm has an important effect on survival[22]: The larger the start-up in terms of employment, the higher the chances of survival. This result is quite common in the literature. We have calculated using the coefficients estimated in (2) that if the firm doubles its size at entry then its hazard rate decreases 9.2%. Turning to the industry control variables, we find that higher industry entry rate at birth year increases significantly the hazard rate of start-ups. This finding supports the idea put forward in the previous section that sectors with high entry rates are usually characterised by high exit rates; some of the displaced firms are old but a large number are new firms that failed to be accepted in the market. This result is also quite common in the literature. On the other hand, industry concentration seems to be positive for survival[23]. Indeed, Weiss (1976) suggested the possibility of survival of suboptimal scale firms in concentrated industries, where the price level is more likely to be high. Although the empirical available evidence is inconclusive in this respect and many papers report a non-significant coefficient for concentration, Callejón and Segarra (2002) also find a positive and significant effect of concentration (proxied by margins) on the survival of new Spanish firms.

As for the sector dummies, we take as a reference the construction sector. Only the coefficients of the utilities and the financial, insurance, real state and business to business sector are significant. The dummy corresponding to the production and distribution of water, gas and electricity is negative, which means that the probability of exit of firms in this sector is lower than that of firms in construction. The coefficient of the business to business sector is positive; firms in this sector survive less than firms in construction.

Focusing now on the firm initial financial characteristics, we find that both initial short-term and long-term debt have significant effects on survival. In particular, an increase in debt, relative to equity, decreases the probability of failure *if* the firm is not too indebted. The effect of debt on survival reverses after some point. We have tested if these effects are significant, obtaining that they are all significant (at 5%) except the effect of increasing long

22. We chose the specification of the log transformation of start-up size because the overall fit improves. This confirms the non-linear relation of start-up size with survival already found in the literature. Note that start-up size is not significant without the logarithmic transformation, as can be seen in model (3).

23. With the exception of model (4) in which there are neither year or sector dummies, and concentration becomes non significant.

term debt when long term debt is above 90%. In this latter case, there are so few observations (less than 1%) that the data are not able to say anything. The turning point ranges, for the case of short-term debt (for which there are enough observations in all segments), from 50% to 75% of indebtedness, depending on the partition considered. What we can say with these results at hand is that debt affects differently survival depending on the indebtedness of the firm, being the effect positive for low levels of leverage.

In order to check for the robustness of this non-monotone relationship between debt and survival, we have also tried a specification where, instead of estimating a different effect of debt on survival in different segments, we postulate a 4^{th} degree polynomial relationship between debt and survival. We consider this specification to be less reliable in the tails than the former, especially for the long term case, where there are few observations for high levels of debt. The polynomial specification confirms that the relation between debt and survival is non-monotone. The point where the sign of the relation reverses could again not be calculated accurately since it is very sensitive to small changes in the coefficients inside their confidence interval.

Lastly, concerning cash holdings, we find that a firm with higher cash ratio at birth have less probability of exit. This effect is, however, not significant at 5% [p-value is 0.063 in model (2)].

In order to assess the magnitude of these effects, we have calculated the impact of raising each type of debt in 5 percentage points on survival of firms with different initial level of indebtedness. The result is reported in table 6, where we also show confidence intervals at a 95% confidence level.

Table 6: Effect on exit probability of a 5 pp. increase in each type of debt for firms with different initial level of indebtedness

Effect of long-term debt on the hazard rate if initial long-term debt is:	**% Observations falling in that category**	**Mean effect**	**Confidence Interval (95%)**	
Below 50%	88.4%	-1.52%	-2.20%	-0.84%
Between 50% and 75%	8.8%	+2.09%	+0.35%	+3.86%
Between 75% and 90%	2.1%	+3.79%	+0.67%	+7.00%
Above 90%	0.7%	+3.72%	-5.14%	+13.40%
Effect of short-term debt on the hazard rate if initial short-term debt is:	**% Observations falling in that category**	**Mean effect**	**Confidence Interval (95%)**	
Below 50%	37.8%	-2.47%	-3.17%	-1.77%
Between 50% and 75%	24.9%	+0.88%	+0.01%	+1.76%
Between 75% and 90%	19.8%	+3.98%	+2.90%	+5.08%
Above 90%	17.5%	+8.08%	+6.37%	+9.81%

The effect of short term debt is much more precisely estimated as it can be seen by its much narrower confidence intervals. The reason is the extremely different distribution of both types of debt. For short term debt, there is a sufficient number of observations in each of the four groups, whereas for long term debt most firms are in the first group. This latter distribution implies a substantially low accuracy of the estimators, as it is shown by the fact that the confidence interval coefficient of long term debt above 90% includes both positive and negative extreme values. Given this limitation, it is difficult to say what type of debt is more important for survival. What is clearer is that our results suggest that holding both types of debt, instead of equity, has positive and important effects on survival up to some point. Beyond this point, further debt increments have a negative impact on survival, and these effects are more important the higher is the corresponding debt ratio or indebtness of the firm.

In summary, our results point to the existence of an important non-linear impact of debt upon survival. The sign of that impact changes depending on the level of initial indebtedness of the firm: If the firm is not too indebted, an increase in debt is good for survival; if the firm is heavily indebted an increase in debt increases the probability of failure.

It could be argued that the initial financial structure of the firm is endogenous, that is, that banks finance with debt only those start-ups that survive longer. For this to be true, we should believe that banks have information prior to the beginning of the firms' operations to assess properly the survival probabilities of the firm. Moreover, we would expect that the relationship between debt and survival is positive. However, we find a negative effect for some segments of both types of debt. In any case, in order to assess the importance of this problem of unobserved heterogeneity, we have estimated model (5), which is like our benchmark model (2), except that the former is controlling for unobserved heterogeneity.[24] The results are very close to the benchmark model, so controlling for unobserved heterogeneity does not alter any of the conclusions.

Sectoral effects could go beyond the ones captured by the industry entry rate, concentration index and aggregated sector dummies (seven main sectors). Furthermore, as it was suggested by Audretsch (1995), what could matter is not so much the start-up size but the gap between the start-up size and the minimum efficient scale of the sector. For these reasons, we have checked whether the results change when two-digit sector dummies, which would capture specific characteristics of the sector such as the minimum efficient scale, are included (around 50 sectors)[25]. One problem that arises when doing so is that we have few observations for some narrowly defined sectors, such as air and spatial transport. For those special cases, we have added their observations to those of closely defined sectors. The grouping we have made is the following: primary sector (10-19); oil refinery and nuclear fuel handling (23) has been added to chemical industries (24); and finally, air and spatial transport (62) has been put together with sea transport (61).

Model (6) in table 5 shows that both the coefficients and the t-statistics do not vary much with respect to the benchmark model (2). The only exception is the loss of significance of the initial cash holdings, which was already not significant at 5%. These results support

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24. We are assuming in model (6) a Gamma distribution of unobserved heterogeneity. The estimation of a discrete distribution involves convergence problems in our data. See, among others, Meyer (1990) for details on the exact procedure we are using to control for unobserved heterogeneity.

25. The inclusion of entry rates and concentration indexes calculated at 2-digit sectors along with the 2-digit sector dummies is fraught with multicollinearity problems. For that reason, when 2-digit sector dummies are included, we exclude the entry rate and concentration index.

the robustness of our previous estimations. Moreover, one could have argued that the significative effects of initial financial conditions could be capturing the different survival patterns present in different sectors (at aggregation level lower than the main 7 main sectors used above) because the optimal financial structure could be different between these sectors. If this was the case, the relation we find between initial financial conditions and survival probabilities would be spurious. The fact that we also found these effects to be significative at 2-digit disaggregation level suggests that the relations are indeed not spurious[26].

5.4 Sectoral analysis

Given the richness of our database we are in position to estimate the impact of the different variables on the probability of exit of firms in different sectors. Table 7 shows the results using a model allowing for a non-linear impact of debt on survival and including year dummies. The model has been estimated separately for the service, construction and industry sector.

One has to be very careful when interpreting the estimations shown in table 7 because the number of observations in each sector varies widely and that affects in a crucial way the accuracy of the coefficients. In spite of that, some interesting results emerge from table 7. First, the start-up size is an important determinant of the probability of survival across all sectors. Its impact, however, is much larger in the service sector than in construction and industry. This could be due to the fact that industrial firms have more tangible assets than service firms. This means that they are able to provide some collateral and, therefore, they could be less financial constrained than service firms.

Holding cash seems to enhance the probability of survival in the construction sector more than in the rest of the sectors, although differences are not significative. With respect to the initial financial structure of firms, there is mild evidence that survival of firms operating in the industry sector are more sensitive to short-term debt holdings than those in the service sector.

Finally, the larger the industry entry rate existing at the time of entry of the firm, the higher the probability of failure in the industry and service sector although differences across sectors are not very significative. What is different across sectors is the impact of the degree of industry concentration on survival. Concentration does not seem to be relevant for survival in the service sector but it has a negative and significant impact in the industry sector. Hence, the average concentration effect found in the aggregate seems to be driven by the industry sector.

26. Or at least the argument should be based on different financial structures at an aggregation level lower than 2-digit which is hard to believe.

Table 7: Estimation results for main sectors

Variable	All sectors	Construction[a)]	Industry	Services
Log of start-up size	0.8674 (-14.5)	0.9328 (-3.15)	0.9451 (-2.73)	0.8177 (-15.42)
Long-term debt	0.9969 (-4.4)	0.9963 (-1.98)	0.9928 (-4.03)	0.9980 (-2.41)
Long-term debt above 50%	1.0072 (3.4)	1.0024 (0.40)	1.0103 (1.82)	1.0068 (2.54)
Long-term debt above 75%	1.0033 (0.93)	0.9847 (-0.96)	1.0014 (0.15)	1.0054 (1.30)
Long-term debt above 90%	0.9999 (-0.01)	1.0686 (0.94)	1.0343 (1.89)	0.9935 (-0.55)
Short-term debt	0.9950 (-6.8)	0.9895 (-5.37)	0.9910 (-4.52)	0.9971 (-3.30)
Short-term debt above 50%	1.0067 (4.9)	1.0104 (3.38)	1.0160 (4.89)	1.0031 (1.78)
Short-term debt above 75%	1.0061 (4.7)	1.0092 (3.67)	1.0076 (2.55)	1.0044 (2.48)
Short-term debt above 90%	1.0078 (5.1)	1.0102 (3.94)	1.0067 (1.82)	1.0070 (3.18)
Cash holdings	0.9991 (-1.9)	0.9978 (-2.09)	0.9989 (-0.83)	0.9995 (-0.85)
Industry entry rate	1.0169 (4.5)		1.0334 (3.53)	1.0438 (11.98)
Industry Concentration	0.9957 (-3.4)		0.9930 (-4.10)	1.0006 (0.36)
Sector dummies	Yes (7 sectors)	No	No	No
Year dummies	Yes	Yes	Yes	Yes
Numer of firms	87767	15055	16805	55907

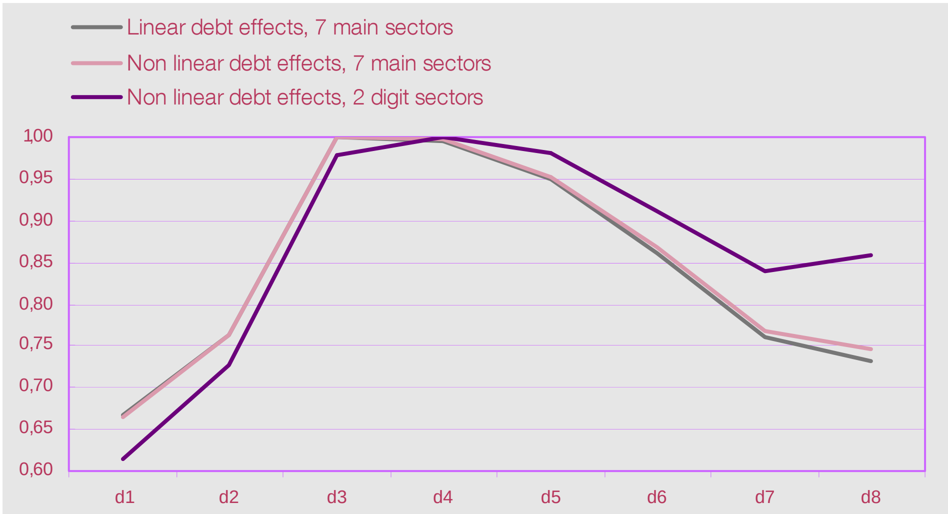
a) Given that construction is composed of only one sector (at 2 digit) level, we have to exclude the sector variables due to multicollinearity problems.

5.5 *The baseline hazard*

In this section we depict the baseline hazard, or the relationship between a firm's exit risk and its age (also known as duration or age dependence) after controlling for the set of explanatory variables introduced previously. In particular, we recover for each of the estimated models the estimators of the age dummies that are implicit in a discrete time proportional hazard model. Please recall from section 5.1 that only the shape of the baseline hazard is informative because it can be re-scaled in any convenient way. Consequently, we have re-scaled each of the estimated baseline hazards so its maximum is 1 in order to be able to compare one with another.

Figure 12 shows the conditional baseline hazard predicted by three of the different models estimated above: Specification (1) in table 5 which assumes a linear effect of debt upon survival and includes dummies for the 7 main sectors of the economy; specification (2) in table 5 which relaxes the linear assumption and also includes 7 sector dummies; specification (5) in table 5 which allows for non-linear effects and controls for 50 sectors (instead of the 7 main sectors).

Figure 12: Conditional baseline hazard, different specifications (a)

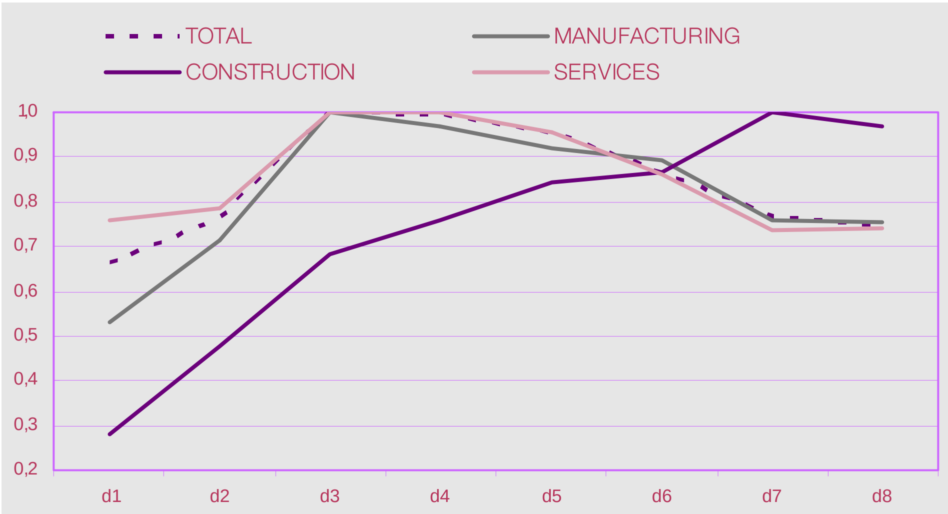


(a) Baseline hazards are re-scaled in such a way that their maximum is 1.

As one can see, the baseline hazard function does not vary much depending on the specification used. Its inverted-U shape, with a maximum at around 4 years, is consistent with the non-parametric or unconditional hazard function estimated in the previous section. In other words, even after controlling for a set of variables we think might affect the probability of failure of a firm, has the hazard function an inverted-U shape. As it was mentioned before, this type of duration dependence has also been found in other countries such as the United States, United Kingdom, Italy or Germany. It responds to what it has been known as the "liability of the adolescence" or the honeymoon effect brought about by stock of the initial resources of the new firm. Those resources help the new firm go through the first years even if the firm results to be inefficient. Once the initial stock of resources is used up, if the firm is inefficient it will exit the market, as predicted by the theoretical learning models.

There are not many studies in Spain attempting to estimate a conditional or unconditional hazard function. The few existing, such as Callejón and Segarra (2002) or Callejón (2003), estimate using data from the Spanish Directory of Firms or DIRCE a monotonically decreasing hazard function for a cohort of Spanish manufacturing firms. In order to be able to compare our results to theirs, we have estimated the baseline hazard function for different sectors, including the manufacturing one.

Figure 13: Conditional baseline hazard by sector (a)



(a) Baseline hazards are re-scaled in such a way that their maximum is 1.

The baseline hazard function for service and manufacturing firms is increasing during the three first years of operations and decrease thereafter. Hence even after restricting our sample to manufacturing firms we find an inverted-U shaped hazard function. In spite of the fact that we use the same source of duration information as Callejón and Segarra (2002), there are many reasons that could explain the differences found in the shape of the hazard. Among them, Callejón and Segarra (2002) have data for groups of firms belonging to a given size range, instead of individual data as we have. Maybe most importantly, they control for a different set of variables and, above all, include the value of some of them at the actual year instead of only at the entry year.

The only sector in Figure 13 showing a slightly different behaviour is construction. The baseline hazard for construction increases up to the seventh year and then starts decreasing. The fact that the peak of the function occurs a bit later could be due to the fact that sunk costs are larger and, therefore, inefficient firms delay as much as possible exit.

6 Conclusion

We have constructed a new database aimed at studying the post-entry survival of firms in Spain. The new database is the result of the combination of several sources of information, and includes data on survival patterns, economic sector of activity and financial and employment variables for a set of around 90,000 firms born between 1995 and 2002 across all sectors of the business economy. Although the database suffers from some problems, mainly the sample bias towards more stable firms, we consider it adequate to analyse the relative importance of the determinants of firm survival.

We have conducted two complementary types of analysis of duration, namely, non parametric and semi-parametric. Concerning the former, we found two interesting results. First, Spanish exit rates are smaller that those in similar countries. This is true across years and sectors, maybe with the exception of the sector including financial, insurance, real state and business to business activities which showed similar patterns of entry and exit than those in nearby countries. This is a finding common to other studies using different sources of data and therefore it is not only due to our possible sample bias. Second, the non-parametric or unconditional hazard function of Spanish firms has an inverted-U shape, and this is true across all sectors of the economy. This latter result can be also found in other countries such as the United States, United Kingdom, Italy or Germany. These two features could be important for employment and productivity growth in Spain, and therefore deserve special attention in future research.

Regarding the semi-parametric analysis, we have estimated a discrete Cox proportional hazard model to assess the partial effect of several variables on the probability of survival. We find that firms that start up bigger have a higher probability of survival. One interpretation of this fact is that firms with better information about their future success enter at a greater size. Another possible interpretation is that firms start small in spite of the fact that it could be more appropriate in some industries to enter at a bigger scale because of the existence of financing constraints. These constraints could be larger in the service sector since our sector analysis shows that start-up size is more important for survival in that sector.

Firms entering in more dynamic and/or less concentrated markets have lower probability of survival. However, the impact of concentration upon survival seems to be driven entirely by what happens in the industry sector since concentration does not play any role in the probability of survival of firms operating in the service sector.

Finally, our results suggest that holding debt, instead of equity, has positive and important effects on survival up to some point. Beyond this point, further debt increments have a negative impact on survival, and this effect is more important the higher is the corresponding debt ratio or indebtness of the firm. One possible interpretation is that the markets in which firms are financing their initial operations are imperfect and/or incomplete given that if markets were perfect, the probability of survival of a firm would depend solely on its profitability, and its initial financial structure would be chosen to ensure this. If this interpretation is correct, financing problems of start-ups could be driving out of the market efficient firms that otherwise would stay, and eventually grow and contribute to aggregate employment and productivity.

This paper has focused on the survival pattern of Spanish firms. But this is only the first step in the analysis of the impact of firm demography on employment and productivity growth. Future research will make use of the BSFDD to explore the role of new, established and exiting firms in the process of job creation and productivity growth.

Annex: The construction of the data set

We have combined information from four different sources to construct the BSFDD. The first and second sources of information are the “Central de Balances Banco de España-Registros Mercantiles”, or CBB, and a database provided by a private firm called Informa. Both sources work with data from the regional registries of firms. As it was mentioned before, all companies in Spain are required by law to deposit their balance sheets and income and expenditures accounts each year in the registries. That means that theoretically we have access to data on total assets and liabilities, and their components, from the balance sheet, as well as to total expenditures and revenues and their components from the income and expenditures account. The firm registries provide also the number of employees and the economic sector in which the firm carries out its main activity. One difference between Informa and the CBB is that the former resorts to additional sources of data to infer as well the entry date of firms in a sample. The sample of Informa for which that information is available consists of about 500,000 firms active any moment between 1992 and 2003.

The third source of information is the Spanish Central Directory of Firms (DIRCE), run by the Spanish National Statistics Institute, which publishes periodically aggregate information on firm demographics in the form of entry and exit rates for different years, sectors and the kind. DIRCE has provided us with firm-level data for a sample of firms. That information consists of a variable for each firm and each year that establishes whether the firm is new (enters)[27], remains, or disappears from the firm registry (exits) over the year. Hence, we use this source to establish the survival pattern of each firm along time. The fact that we have access to both the aggregate data covering all the population of firms published periodically by DIRCE, as well as individual data for our limited set of firms has allowed us to use the aggregate data as a benchmark to compare several statistics of our sample.

Finally, the fourth source of information is fiscal data provided by the Spanish Tax Agency, which is only used to improve the estimation of firms’ exit date.

The Bank of Spain Firm Demography Database or BSFDD, is the result of the combination of the information provided by these four different sources. The combination procedure was as follows. First, using the firms’ entry date provided by Informa we selected each year those firms born that year or before and identified them using their fiscal identification number. Then, in second place, we made a special request to DIRCE in order to obtain the individual data necessary to infer the survival pattern of each firm. Our request did not intend to be comprehensive but rather was limited to the firms selected according to their entry date. Given that DIRCE started tracking systematically firms from 1995 on, we got duration information for about 300,000 firms born between 1995 and 2002.

The micro data provided by DIRCE is therefore the basis for our survival pattern. We developed, however, several depuration mechanisms to spot firms with no activity that were still in the registry. In particular, we constructed two filters. The first one used the assets and profits information provided by Informa and the CBB to identify if a firm was still registered

27. DIRCE carries out some additional depurations in order to distinguish pure births from reactivations.

in DIRCE, but had little or none economic activity[28]. Those firms detected as inactive had their status changed from continuing to exiting firm. Given that several firms did not report any asset or sales data at all, we fear there could be more undetected cases in the data set. The second filter included the fiscal information provided by the Spanish Tax Agency. The filter changed again the status from continuing to exiting of those firms that had dropped out from the fiscal registry in any given year but still appeared in the DIRCE registry.

After using the filters, we restricted the sample to firms with a complete data set in terms of sector, legal form, start-up size and initial financial structure. The result is a representative sample of around 90,000 firms born between 1995 and 2002 across all sectors of the business economy.

28. We define inactivity as a function of two variables, profits and total assets. A firm is marked as inactive if either profits are exactly equal to zero or both profits and assets are exactly equal to profits and assets of the previous period.

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