Comparison of Firm Dynamics in High-Tech and Low-Tech Firms: The Role of Innovation on Survival

Rui André Pereira Agostinho

Thesis to obtain the Master of Science Degree in

Industrial Engineering and Management

Supervisor: Prof. Hugo Miguel Fragoso de Castro Silva

Examination Committee

Chairman: Prof. Miguel Simões Torres Preto

Supervisor: Prof. Hugo Miguel Fragoso de Castro Silva

Members of the Committee: Prof. António Sérgio Constantino Folgado Ribeiro

November 2019

Resumo

A sobrevivência e o crescimento das empresas são fatores fundamentais para compreender o crescimento económico, em qualquer indústria. A influência das dinâmicas de empresas e da indústria na sobrevivência de empresas na indústria de manufatura portuguesa já foi previamente estudada (Correia & Gouveia, 2006; Mata & Cabral, 2003; Mata & Portugal, 1994), mas a literatura que relaciona estas dinâmicas com o efeito da intensidade tecnológica da indústria é escassa. Assim sendo, de forma a preencher esta lacuna, o principal objetivo desta dissertação é estudar como a sobrevivência de empresas na indústria de manufatura em Portugal difere para empresas em ambientes de alta e baixa tecnologias, com especial enfâse no impacto provocado pelo investimento em inovação. Para tal, usamos o Sistema de Contas Integradas das Empresas, fornecido pelo Instituto Nacional de Estatística. De modo a estudar a sobrevivência das empresas na nossa amostra de interesse, estimamos modelos de duração com *proportional hazards*, usando uma função de *baseline hazard* constante por segmentos — *piecewise constant*. Analisamos alguns dos determinantes da sobrevivência de empresas mais relevantes na literatura, tais como a intensidade tecnológica da indústria, idade da empresa, número de trabalhadores atual, número de trabalhadores aquando da formação da empresa, investimento em inovação e investimento em exportações. Os nossos resultados revelam que o impacto da idade das empresas no *hazard* de fecho é descrito por um aumento dos *hazards* durante um período inicial, que de seguida decrescem monotonicamente, o que vai de acordo com a teoria designada de "*liability of adolescence*". Mostramos também que tanto empresas que apresentam maior tamanho atual, como empresas que apresentam maior tamanho aquando da sua formação apresentam menor *hazard* de saída do que as empresas de menor dimensão existentes na indústria. Os resultados também sugerem que empresas inovadoras apresentam menor *hazard* de saída do que empresas que não inovam, e a mesma relação existe para empresas exportadoras em relação a empresas não exportadoras. Em relação ao impacto da intensidade tecnológica, indicamos que firmas em ambientes de alta tecnologia possuem menor *hazard* de saída que empresas em ambientes de baixa tecnologia. Mostramos também que as empresas em ambientes de alta tecnologia beneficiam mais em ser inovadoras do que em ambientes de baixa tecnologia. Por último, não podemos afirmar que exista uma diferença no *hazard* de saída associada à relação entre o tamanho das empresas e a intensidade tecnológica. Como referido, o estudo do impacto que a intensidade tecnológica tem na sobrevivência de empresas não foi estudado profundamente na indústria de manufatura portuguesa, e o mesmo se aplica para o estudo de como o impacto das dinâmicas de empresas difere para diferentes níveis de intensidade tecnológica. Assim sendo, cremos que os nossos resultados são relevantes, visto traçarmos conclusões relativas a estes tópicos previamente pouco estudados.

Palavras chave: sobrevivência; *hazard*; indústria de manufatura portuguesa; intensidade tecnológica; inovação; exportações.

Abstract

The impact of firm dynamics on the survival of firms is a topic that has been broadly studied for several decades. In fact, both firm survival and firm growth are fundamental factors that need to be considered in order to understand how economic growth is characterized in any industry. The influence of firm and industry dynamics on the survivability of firms in the Portuguese manufacturing industry has already been studied (Correia & Gouveia, 2016; Mata & Cabral, 2003; Mata & Portugal, 1994), but the literature on the matter that relates such dynamics to the effects of the technological intensity of the industry is lacking. As such, in order to fill this gap, the main objective of this dissertation is to study how the survival of firms in the Portuguese manufacturing industry is different for firms that are inserted in environments with high and low technological intensities, with a special emphasis put on the impact of investment in innovation. To perform this study, we use the Integrated Business Accounts System (*Sistema de Contas Integradas de Empresas* – SCIE) dataset, provided by the Portuguese Institute of Statistics. In order to study the survival of firms in our sample of interest, we estimate proportional hazards duration models, using a piecewise constant function, in which the baseline hazard was modelled in segments that we consider to be constant. We analyse some of the most relevant characteristics of firm survival, as discussed in the literature, such as the industry's technological intensity, firm age, current number of employees, number of employees at start-up, investment in innovation and investment in exports. We reveal that the impact of firm age in the exit hazard is described by an increase on the exit hazards during an initial period, which then decrease monotonically, following a theory called "the liability of adolescence". We also show that both for firms that present larger current number of employees and for firms that present larger number of employees at start-up, the hazards of exit are lower than when compared with their smaller counterparts. Our results also suggest that firms that are innovators present lower hazards of exit than those that are not innovators, and the same relation exists between firms who are exporters and those that are not. Regarding the impact of technological intensity, we find that firms in high-tech industries face lower hazards of exit than in low-tech ones. Furthermore, our results indicate that firms benefit more from being innovators in high-tech industries than in low-tech ones. Lastly, we cannot ascertain if there exists a difference in the hazards of exit associated with the relationship between firm size and technological intensity. As we stated, the study of the impact that technological intensity has on firm survival has not been studied deeply in the Portuguese manufacturing industry, and the same applies for how the impact of firm dynamics is different for different levels of technological intensity. As such, we believe our results to be relevant, as we draw conclusions on these previously less studied topics.

Keywords: survival; hazard; Portuguese manufacturing industry; technological intensity; innovation; exports.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

GDP - Gross Domestic Product

MES - Minimum Efficient Scale

NACE - Statistical Classification of Economic Activities in the European Community (from the French term "*Nomenclature Statistique des Activités Économiques dans la Communauté Européenne*")

OECD - Organisation for Economic Co-operation and Development

SCIE - Integrated Business Accounts System **(***Sistema de Contas Integradas de Empresas*)

1 - Introduction

Firm survival, and the various factors that influence it, has been broadly studied in the last decades, as it allows researchers to understand what are the characteristics of firms that allow them to have good business capabilities and to prosper in an industry. Most of these studies were of empirical basis, analysing which aspects of firm and industry dynamics affect the survival and growth of companies, using different sources of data. Industry and market characteristics, as well as the characteristics of the firms themselves, were the focus of most studies (Audretsch, 1995; Cefis & Marsili, 2006; Hall, 1987; Mahmood, 2000; Mata & Portugal, 2002). The relationship between these factors and survival is important, as the decision to create a firm is not independent of the probability of survival in the industry, and the likelihood of survival is conditional upon a firm having already entered an industry (Audretsch, 1991).

This dissertation analyses the impact that the characteristics of firms have on firm survival, comparing firm dynamics of high-technology and low-technology firms. Firm dynamics in the Portuguese manufacturing industry have already been studied by, for example, Mata & Cabral (2003), Mata & Portugal (1994) and Correia & Gouveia (2016). However, the previous works do not focus on the influence that technological intensity has on the Portuguese market. Our main goal is to fill this gap, by studying how the survival of firms in the Portuguese manufacturing industry is different for firms that are inserted in environments with high and low technological intensity, with a special emphasis on the impact of innovation on survival. Besides the influence of technological intensity and innovation, we also study the impact that firm age, current firm size, firm start-up size and exports have on firm survival.

In order to perform this study, we estimated proportional hazards duration models, using a piecewise constant function. For this function, the baseline hazard is modelled in segments where we assume the hazard is constant. The dataset used in our study was the Integrated Business Accounts System *(Sistema de Contas Integradas de Empresas* – SCIE), provided by the Portuguese Institute of Statistics.

Our main findings are that the survival probabilities are greater for larger firms and for firms that start at larger sizes. We also find that innovators and exporters present lower hazards of exit than non-innovators and non-exporters. These findings are in line with the findings of the relevant literature (Audretsch, 1995; Bruderl et al., 1992; Cefis & Marsili, 2006; Dunne & Hughes, 1994; Wagner, 1995). Regarding firm age, we find that the hazards of exit firms face grow during their initial period of activity, and then decrease monotonically, following a theory called the “liability of adolescence” (Bruderl & Schussler, 1990; Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991). When technological intensity is considered, our findings suggest that firms in high-tech environments face lower hazards of exit than those in low-tech ones. Such results are not in line with the findings in the literature, that state that the opposite is the most common scenario (Audretsch & Mahmood, 1994). Our results also suggest that firms benefit more from being innovators in high-tech industries than in low-tech ones, as expected, considering that high-tech environments are associated with greater uncertainty and technological obsolescence, making innovation crucial (Agarwal & Gort, 2002; Audrestch & Mahmood, 1994). Lastly, we tested if small firms face lower hazards of exit in high-tech industries than in low-tech ones, but we could not draw a definitive answer from our results.

We believe our findings to be relevant, since this dissertation focuses on the importance that technological intensity has on firm survival, providing some explanations regarding why the survivability of firms differs between environments characterized by different levels of technological intensities. Furthermore, our results also give some insight on how the impact of firm dynamics is different for high-tech and low-tech firms, particularly when regarding the impact of investment in innovative activities. Considering these topics have not been studied deeply in the Portuguese manufacturing industry, our study helps fill this particular gap.

2 - Problem Definition

2.1 - Overall context

In most industries the level of uncertainty tends to be high, as new companies enter it and others leave it on a regular basis. There are several reasons for a company to make the decision to leave an industry, and various factors influence the survival rate of firms. The Portuguese market is no exception to this general rule. Mata and Portugal (1994) state that the survival rate of most entrants is low and even successful entrants take more than a decade to achieve a size comparable to the average incumbent. This perfectly describes the Portuguese market. In fact, in their study (in which they follow firms created in the Portuguese manufacturing sector in 1983) almost one half of the firms created failed within only four years of their birth, with about 20% failing within their first year alone.

Many studies have identified the factors that influence firm survival and growth in different industries (for example, Audretsch, 1995; Audretsch & Mahmood, 1994; Gort & Klepper, 1982; Mata & Portugal, 1994). Firm survival and growth tend to be viewed as extremely important topics of study, as they are two main characteristics of any industry. Their study allows us to understand why some firms have superior business performances and why they are more fit to prosper within the industrial environment, when compared to other firms that do not grow, decline, and eventually end up not surviving.

Why do firms exit an industry? This is the fundamental question that aims to be answered by all the studies in the area. Audretsch and Mahmood (1994) found that the probability of a firm exiting an industry tends to increase as the gap between its output levels and the minimum efficient scale (MES) level of output in that industry increases. If the MES level of output is higher than the firm's own output level, this leads to the existence of a cost disadvantage, which will increase the risk of failure. Due to this interdependence, as the gap increases, the cost disadvantage that firms face increases accordingly, and so does the likelihood of exit. They also affirm that the smaller the firm, the larger their cost disadvantage will be. As such, the study of how this relationship between firm dynamics and survival works is crucial to identify the reasons for a firm's success and failure.

Most of the studies undertaken so far were empirical and aimed at finding how the characteristics of an industry and its surroundings, as well as characteristics of the firms themselves would affect the survival prospects of firms in those industries. The majority focused their work on specific datasets of companies in the industry they were researching, analysing and interpreting the data provided, to try and answer such questions. Some examples of studies focusing on different industries include: Acs and Audretsch (1987) – the authors study how innovative activity affects small and large firms differently, for all the industries catalogued in the U.S. Business Administration; Esteve-Pérez and Mañez-Castillejo (2008) – the authors use a yearly survey of the Spanish manufacturing firms that were created in 1990 to study the determinants of firm survival; Mata and Portugal (1994) – the authors study the determinants of the survivability of Portuguese manufacturing firms created in 1983.

Several factors have been studied, and their relationships with survival and growth of firms, both at the firm and industry level. At firm level the main factors studied have been firm size, with particular relevance to start-up size and age. All of these factors are positively related with firm survival, meaning that the young and small firms are the ones that most commonly leave the industries (Brudlerl et al., 1992; Cefis & Marsili, 2006; Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Geroski, 1995; Hall, 1987; Mata & Portugal, 1994).

At the industry level, the technological intensity and life cycle of the industry are factors that are usually portrayed as having a significant impact on a firm's survival. Industries characterized by high technological intensity are associated with lower chances of survival for firms (Audretsch, 1995; Audretsch & Mahmood, 1994; Gort & Klepper, 1982; Mata & Portugal, 1994).

Some topics that have been approached with special detail include:

- The relationship of firm size and survival, trying to ascertain under which conditions small firm survival prospects are higher or lower, and the same for their larger counterparts (Audretsh et al., 2006; Caves & Porter, 1977; Porter, 1979).

- The relationship between firm age and survival, studying how the probability of failure changes with the aging of firms in an industry (Audretsch et al., 2006; Audretsch & Mahmood, 1995; Bruderl & Schussler, 1990; Cefis & Marsili, 2006; Esteve-Pérez & Mañez-Castillejo, 2008).

- How technological intensity in an industry affects the survival chances of the firms in it, and the differences on how this effect takes place for firms with different characteristics (Agarwal and Audretsch, 2001; Audretsch & Mahmood, 1994).

One more factor that influences firm survival is if a firm is an exporting firm, or if it is exclusively domestic. Exporting firms have access to some advantages that non-exporting ones do not, such as being able to spread sales over different markets and countries, spreading the risk associated (Wagner, 1995). However, only the most well adapted firms will be able to take full advantage of it, which relates the decision to export or not to export with good management and adaptation skills (Wagner, 2012).

Additionally, other studies focused their attention on the presence of another important factor: innovative activities carried out by the firms. The presence of such innovative activities can play an extremely important role in the survival and adaptability of firms, true for both newcomers and incumbents. For newcomers, however, the risk of failure is significantly higher in the first few years of activity, and successful means of innovation usually lead to greater prospects of survival (Audretsch, 1995; Cefis & Marsili, 2006). Through innovation, firms are better able to deal with new disruptive technologies, improving the capabilities they already possess (Banbury & Mitchell, 1995).

Due to this, innovation may be essential for the survival of firms in any industry, and studies have tried to understand just how exactly the interaction between firm survival and growth and innovative activity takes place. Some of the topics that have been studied include:

- How innovation affects small and large firms differently, and why there is such a difference (Caves & Porter, 1977; Porter, 1979).

- How the presence of an innovative environment affects survival prospects (Christensen, 1977; Gort & Klepper, 1982; Utterback & Abernathy, 1975).

- How the characteristics of innovation change with the stages of the life cycle of an industry, and how it relates to firm survival (Audretsch, 1991; Gort & Klepper, 1982; Nelson & Winter, 1982).

- How the technological intensity of the industry affects innovation, and how it relates to firm survival (Agarwal & Gort, 2002; Agarwal & Audretsch, 2001; Audretsch & Mahmood, 1994).

In this dissertation, in order to analyse the survival of firms in the Portuguese manufacturing industry, we use the aforementioned topics discussed in the literature as guidelines for our study. The questions we aim to answer with this study are discussed in the following section.

2.2 - Research questions

As previously mentioned, the relationship between firm and industry dynamics and the survival probability of firms is a matter of high importance when trying to understand how the evolution of industries takes place, namely what are the reasons that lead to the success or failure of firms in them. Besides this, as pointed out, the presence of successful innovative activities can affect the survival of firms in any industry, whether they are new entrants, or already well-established firms (Caves, 1998). Following what has been done in many of the previous studies, these topics are the core concepts of this dissertation.

Some studies on the matter have already been undertaken in the Portuguese market. Mata and Portugal (1994) followed the Portuguese manufacturing companies in 1983 and studied the determinants of their lifetime, evaluating the impact that industry and firm specific variables have on survival. Firm start-up size and number of plants were found to impact survival positively and industry entry rate to impact it negatively. On another study Mata & Portugal (1999) evaluate the effect of technological conditions on firm survival, splitting firms into three groups of high, medium and low technology intensity, following

OECD's categorization. They find that industries with higher technological intensity exhibit lower mortality and benefit more from a larger start-up size. On the same study they also find that entrants in expanding industries have better survival prospects.

Therefore, in this dissertation we continue along a similar path of the previously mentioned studies, by analysing the impact of firm and industry dynamics in the Portuguese manufacturing industry. In particular, we focus on the impact innovative activities have in firm survival and how the presence of different technological intensities affects this relationship. Such subjects have not been studied with an emphasis on the Portuguese market.

We use the Integrated Business Accounts System (*Sistema de Contas Integradas de Empresas* – SCIE), dataset provided by the Portuguese Institute of Statistics, focusing on data between the years of 2007 and 2015.

Some of the important points we aim to study in this dissertation are:

- Do small firms always face a lower probability of survival than large firms?
- Does the probability of failure decrease monotonically as firms age, or are there increases and decreases in the probability of failure with the aging of firms?
- How does the start-up size of firms affect the probability of survival?
- Do innovative firms face lower risks of failure than those who do not?
- Does innovative activity affect small and large firms differently?
- Do firms that export face lower risks of failure than those who do not?
- Does technological intensity change the way innovation affects the survival probability of firms, and does it impact smaller and larger firms differently?

2.3 - Organization of chapters

This dissertation is composed of six chapters. The introduction aims to contextualize the problem, portraying what the main research question is, and what are the motivational aspects that are the reason behind this study, discussing and relating them to what has previously been studied in the existing literature. In Chapter 2 we give the overall context of the dissertation, characterizing to a deeper extent the problem to be studied, explaining the research questions on hand. The chapter ends with a short description of the organization of the dissertation. Chapter 3 presents a review of the existent literature on the matter, discussing the main points of previous research. We explore the core concepts, definitions and results of previous studies, while presenting an overview of the firm and industry dynamics, and how they affect the survival and growth of firms. Furthermore, a special focus is given to the concept of innovation, and its relationship with the industry life cycles and technological intensities. In Chapter 4 we define the core variables of our study, and then present the research hypotheses we construct. We also describe the methodology of empirical research that we follow, explaining how we analyse the data. We then describe the dataset we use in our study, and elucidate how we construct our sample of interest. Furthermore, we present the characteristics of the sample, performing a descriptive, preliminary analysis of our sample. In Chapter 5 we present our econometric results, discussing them while considering the important findings discussed on the literature review. Lastly, Chapter 6 provides the concluding remarks, presenting a brief summary of the core findings we obtained throughout the present dissertation.

3 - Theoretical Framework

3.1 - Firm and industry dynamics

3.1.1 - Firm size and age, and their relation to survival and growth rate

Firm size and age are the traditional firm dynamics components that were more amply studied, regarding how they impact the survival of firms, with research showing that both are important predictors of firm survival.

The central, most well supported finding regarding this matter is that, within an industry, smaller firms grow at a faster pace than larger ones, and that they are also more likely to fail. In this sense, both age and size are connected with the survival probabilities of new firms entering the market. Many studies (for example, Audretsch et al., 2006; Cefis & Marsili, 2006; Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Hall, 1987) point to this central idea, stating that firm survival is influenced by both age and size, with the ones most likely to leave the market being the young and small ones.

One of the central theories related to these characteristics of firm dynamics, and how they relate with the survival prospects of firms is the theory of “noisy selection” proposed by Jovanovic (1982). According to Jovanovic, firms are, in general, small when they start, for reasons such as liquidity constraints and imperfect knowledge of their own capabilities. Firms enter an industry without complete information on how efficient and successful they will be. Due to this, the initial presence of firms in the market can be regarded as a trial period during which firms acquire new information about their abilities. However, after the initial period of activity, it becomes increasingly clear for each firm just how efficient they are. As such, according to the theory of “noisy selection”, firms learn about their efficiency by operating in the industry, with the most efficient ones growing and surviving, and the less efficient participants failing and declining (Jovanovic, 1982). The theory also helps explain why small firms have higher rates of failure, as these are mostly firms that entered the market but could not achieve the necessary efficiency, leading them to leave while still at a small size.

Following this statement that relates size and age with firm survival, many other studies present findings on the matter: Geroski (1995) points out that both size and age are correlated with the survival and growth of entrants, finding that the exit rate is higher among smaller firms, and tends to go down significantly as the companies grow in size. Audretsch and Mahmood (1995) also arrive to similar conclusions, suggesting that both firm size and age are correlated, and that while external factors such as scale economies and product differentiation can constitute serious barriers to survival, their impact is weakened with the age of the company.

A number of factors suggest this positive relationship between size and the survival probability of firms. Audretsch and Mahmood (1994) propose that the probability of a firm exiting an industry tends to increase as the gap between their output levels and the minimum efficient scale (MES) level of output in that industry increases. When the MES level of output is higher than the firm's output level, it will lead to the existence of a cost disadvantage, increasing the risk of failure. The authors also found that the smaller the firm, the larger the cost disadvantage will be. This will make them more vulnerable to failure than larger firms, since the smaller ones produce at lower scales. Additionally, Esteve-Pérez and Mañez-Castillejo (2008) state that larger firms are often more diversified than small firms. In particular, the authors find that diversification protects firms in troubled times: if adverse conditions on a particular industry arise, these can be offset by better conditions on other industries, a privilege rarely achievable by smaller firms. Furthermore, the authors suggest that larger firms may have other benefits at their disposal, such as easier access to capital, better tax conditions, and being in better positions to recruit skilled employees.

All the studies mentioned so far point out to the general finding that firm failure rates decrease with the age of firms, with the initial period of a firm's life being the one characterized by a higher failure rate. This is defined as the "liability of newness". However, other studies arrived at different conclusions, stating that new firm hazard rates follow an inverted-U shape pattern — an hypothesis called "liability of adolescence": for the initial period, the hazard rate is low, and the end of adolescence is marked by an hazard maximum followed by monotonically declining hazard rates (Brüderl & Schüssler, 1990; Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991). The liability of adolescence may be explained by the fact that, initially, new firms are able to survive with low risk of failure by using the initial stocks of endowment acquired at the moment of founding. Besides this, decision makers are often still doing initial monitoring on the firms' performances, and it may take a certain period of time to distinguish between systematic and random components of performance. All these factors may postpone judgment about a firm's possible success or failure. However, after the initial resources are used up and the initial monitoring has ended, if firms do not find success, the correct decision may be to exit the industry. This will lead to higher closure rates on the years immediately after the first few of activity, since only companies that are better adapted in the industry will survive, with the others being forced to leave (Mata & Portugal, 2002).

Another hypothesis that has been proposed on the matter is the called "liability of senescence". This hypothesis states that, when reaching advanced ages, older firms are prone to suffer from higher failure rates, as they are highly inertial, becoming susceptible to changes in the competitive environment. According to this hypothesis, beyond a certain age, failure rates are expected to rise once more (Hannan, 1998).

3.1.2 - Start-up size

Another important factor highlighted by many studies is the relation between survival and start-up size. Intuitively, a larger start-up size will lead to better chances of survival, as companies will have more resources available and better ways of competing in the industry. Brüderl et al. (1992) find that start-up size (be it the number of employees, the financial capital invested, or the firm's legal form) is a relevant determinant of survival, with companies that start at larger scales having better prospects of longevity.

Mata and Portugal (1994) find that new firm failure varies negatively with firm start-up size and with the number of plants operated by the firm. The authors reveal that firms that entered the market with more than one establishment are much less concentrated in the smaller size classes than single plant entrants, with the former having higher survival rates than the latter. The authors suggest that this relationship may be related with the fact that small firms often employ less able managers, making them more vulnerable to leaving the market when adverse conditions arise. Mata and Portugal's (1994) results clearly indicate this: almost 50% of the Portuguese firms did not survive until the age of four, and 20% fail in the first year. However, when initial size is taken into consideration, the results are different: among firms created with one or two employees, 30% failed within the first year, but firms created with 100 or more employees had a 95% chance of survival.

We should point out that Mata et al. (1995) state that current size is a better predictor of the survival prospects of a firm than initial size, even when the landscape around the firms remains unchanged. Current size contains information on how a firm reacts to the success it has on the industry over time, and, comparing the power of current versus initial size, Mata et al. find that the empirical models with current size better predict survival prospects.

3.2 – Innovation and innovative opportunities

3.2.1 - The role of innovation

The Small Business Administration defines an innovation as "a process that begins with an invention, proceeds with the development of the invention, and results in the introduction of a new product, process or service to the industry" (Edwards & Gordon, 1984, p. 1). As such, an incredibly important characteristic of firms is the ability to innovate successfully. In fact, innovative developments by firms are generally viewed as a characteristic that boosts their capabilities of development and survival. For instance, firms that successfully achieve product innovation are more capable of offering a good or service that is new or different in some way, and that better goes in accordance with the needs of the potential costumers, differentiating themselves from the competitors. As such, having this competitive advantage gives firms an opportunity to obtain new customers, and to retain the ones they already have (Audretsch, 1995).

Most studies point in the direction of innovation boosting survival chances. In the vast majority of scenarios, the presence of innovative activity is positively correlated with the survival rates of firms. In fact, Geroski (1995) finds that entrants that successfully innovate have higher likelihood of surviving than those who do not. Audretsch (1995) affirms that for firms who have survived the initial period of their existence, innovative activity leads to consistently higher survival rates and higher growth rates.

Hall et al. (1986) assert that firms with a larger portion of their assets in R&D are less likely to leave the industry. They develop this further, by also stating that R&D expenditures (a common measure of innovation) are a more important predictor of growth in the immediate future than expenditure on physical capital. As such, Hall et al. declare that higher R&D investments are related to higher survival probabilities. The authors argue that R&D might be more highly correlated with future success of the firm, both because it is more forward-looking, and because R&D expenditures at the firm level tend to be substantially less volatile over time than expenditures on physical capital.

Innovating may be especially important for the small and young firms, as they need to distinguish themselves from their competitors in order to grow and survive in the industry. As firms enter the industry, most will have low market shares, and a way of increasing their survival chances is by offering a new product or service. In fact, even though young and small firms are the most susceptible to leave the industry, they are also the ones that have the most to gain from engaging in innovative activities (Audretsch, 1991). While holding the total amount of innovative activity in the industry constant, an increase in the ability of small firms to innovate leads to higher survival rates. By contrast, when the small-firm innovation rate is relatively low, the survival rates tend to be lower. Following this, Cefis and Marsili (2006) encounter an innovation premium, which is larger for small firms than for large ones — while the ability to innovate increases survival probabilities for all firms across sectors, the small and young ones that do innovate have a 23% greater chance of surviving than those who do not. Cefis and Marsili (2005) reveal that the opposite also seems to be true, as small firms who fail to successfully innovate have the lowest survival probabilities: in their data, the effect of innovation on firm survival is of 3% for old firms, 5% for grown-up firms, and of 6% for young firms, on average.

It is important to note, however, that developing successful innovative activities leads to an advantage for both newcomers and incumbents, although differently. For incumbents, innovation allows them to overcome possible threats of disruption by new technologies, boosting survival chances (Christensen, 1997; Gort & Klepper, 1982).

Furthermore, innovative advantage is unequivocally associated neither with large nor small firms, with both experiencing higher survival chances when successful innovation takes place. For the case of large firms, Rothwell (1989) finds that the innovative advantages are mainly associated with them having greater financial and technological resources, making them material advantages. Regarding small firms, the author affirms that the advantages are related to entrepreneurial dynamism, internal flexibility and responsiveness to changing circumstances, making them behavioural advantages.

Acs and Audretsch (1987) have findings that also go in accordance with this difference between large and small firms, as far as innovation is concerned. They state that large firms have the relative innovative advantage in industries characterized by being capital-intensive, concentrated and advertising-intensive, while small firms have the relative innovative advantage in highly innovative industries, and in industries that have a high portion of large firms.

However, even though innovation is many times essential for the success of a firm, on the other hand, the presence of a highly innovative environment lowers the probability of success of entrants, when compared to environments where innovative activity is not so crucial. Audretsch (1995) acknowledges that the likelihood of survival is systematically lower in industries where the innovative opportunities available to small industries tend to be the greatest, meaning that a barrier is created by a highly innovative environment, for the first few years of existence of a company. Audretsch and Mahmood (1994) also find, in the case of the US economy and employing industry variables as their explanatory variables, that firms last longer in industries where innovation and R&D play less important roles. Geroski (1995) is also in line with this when stating that the nature of entry barriers means that entry contests may take on the character of a war of attrition. For firms that are unable to adjust, the highly innovative environment ends up being a siren call, and the lure of a differentiated and innovative product becomes the force driving the unsuccessful entrants out of the industry.

In fact, as mentioned by Jovanovic (1982), upon entering an industry, the way of firms learning about their efficiency is by operating in it. It is now possible to understand why the notion of innovative activity is such a core concept in Jovanonic's theory of noisy selection: firms who are efficient enough manage to survive, while the rest will decline and eventually fail. It is not always evident for an entrepreneur if a firm will be able to innovate with good results or not, but this becomes clearer with the passage of time. Firms that successfully innovate can expect future sales growth, while those who fail to do so are more likely to exit from the industry. Taking this into account means that firms usually begin at a small scale of output and then, if they can achieve good results in their activities, are more prone to grow (Pakes & Ericson, 1998).

Ericson and Pakes (1995) propose a model of active learning, where firms learn through their activities. They suggest that firms invest to enhance profit-earning capabilities in an environment characterized by substantial competitive pressure from both within and outside the industry. The outcome of the investment, the success of other firms in the industry, and the competitive pressure determine the success of the firms. If the results are shown to be negative, the choice of exit may be the correct one, leading to the assumption that the process of exit is the outcome of an optimization process. Therefore, firms can speed up the process of learning by investing in R&D, which closely associates with innovative activity.

After some years have passed since the entrance of a firm, a reversed relationship between the innovative environment and the likelihood of survival can be observed. Geroski (1995) reveals that having survived the initial period of time subsequent to entry of eight years, the surviving entrants have, at least to some extent, successfully adjusted and are now able to produce a viable product. What was then a hostile environment and ultimately a barrier to survival to the exiting firms is now a mechanism for promoting the survival of the remaining firms.

3.2.2 - Impact of industry life cycle on innovation and survival and its relation to technological intensity

When considering an industry to study, the life cycles that constitute it, and the different characteristics of each, we need to consider factors that impact the survival of firms in said industry. In fact, industry attributes include several variables that influence firms over time, and even across different industries. Such variables that operate over time are defined by the life cycle of the industry, that will affect, among others, the characteristics of demand (Agarwal, 1998; Agarwal & Gort, 2002).

Agarwal and Gort (2002) found that the stage of the industry life cycle impacts the chances of survival of firms: in the early years of an industry life cycle, technological opportunities for innovation are the highest, but decline as the industry matures. Innovations then shift to minor product refinements and cost reduction, which intensifies competition, leading to higher rates of firm death. Agarwal and Gort also reveal that hazard rate curves flatten as markets mature, which they attribute to firms not depending as much on trial and error, as they can hire skilled labour with previous related experience.

Therefore, innovation is affected by the industry's life cycle, and this cannot be ignored when studying the survival prospects of firms, as the necessary knowledge companies must have changes with the life cycle: while in the earlier stages innovation mostly comes from non-standardized knowledge, in later stages, innovative activities that generate advantage are often heavily routinized (Agarwal & Audretsch, 2001). This difference in the underlying knowledge conditions was first hypothesized by Nelson and Winter (1982) and Gort and Klepper (1982), relating it with the technological conditions of the industry, and with the capacity of firms to innovate and consequently survive. We discuss the relationship between technological intensity and firm survival in further detail in the following section.

Nelson and Winter (1982) define what is known as a technological regime and divide this into two distinct categories, the entrepreneurial regime, and the routinized regime. The entrepreneurial regime is one that is favourable to innovative entry and unfavourable to innovative activity by established firms, while the routinized regime is one in which the conditions are the other way around. The role of innovation also varies between the entrepreneurial and routinized regimes, as they correspond to the early and mature life cycles of an industry, respectively.

One must be aware though, that this definition of technological regime is not easily measurable, as it is a purely theoretical approach to the matter. However, the existence of these regimes may be confirmed, and the distinct regimes can be inferred, to some extent, by just how much small firms are able to innovate, when compared to the overall innovation within an industry. In this sense, when small-firm innovation rate is high relative to the total innovation rate, the technological and knowledge conditions are more likely to reflect the entrepreneurial regime. The routinized regime is more likely to exhibit a low small-firm innovation rate relative to the total innovation rate (Acs & Audretsch, 1988; Audretsch, 1991).

On the other hand, Gort and Kleeper (1982) found evidence that the relative innovative advantage between new entrants and firms already established in the industry depends upon the source of information leading to innovative activity: if information based on non-transferable experience in the industry is crucial to allow for innovative activity, then established firms tend to have the innovative advantage over newer ones; if information outside of the industry is relatively important to create innovative activity, newly established firms will tend to have the innovative advantage. Such an impact influences the survival prospects of firms: incumbents have higher survival probabilities when information based on non-transferable experience in the industry is more relevant than when information outside of the industry is relatively important to create innovative activity, and new entrants have higher survival probabilities when the opposite scenario is true.

3.2.3 - Impact of technological environment

One important topic to take into account when studying firm survival is the impact that the technological environment has in the decision of a firm to exit the market. Agarwal and Gort (2002) define technological intensiveness as the employment of human skills associated with scientific development, relating it with the rate of technological change. Technological change leads to obsolescence, and the more technologically intensive an industry is, the higher the rates of obsolescence of older technologies. Due to this, Agarwal and Gort hypothesize that high rates of technological change will lead to lower survival probabilities for both new firms and incumbents, and their results support this idea, indicating a positive relation between technology intensity and hazard rates.

Audretsch and Mahmood (1994) find that R&D intensiveness associated with a high-tech environment increases the amount of financial requirements needed to survive in an industry, which will increase the hazard rate. Furthermore, an environment characterized by frequent product innovation can be associated with greater uncertainty. As this technological uncertainty rises, the probability that a firm will be able to produce a viable and desirable product will decrease, along with their chances of survival.

It appears that the technological environment shapes the survival rates of small and large firms differently. Caves and Porter (1977) and Porter (1979) argue that by occupying specific strategic niches, it is possible for firms to remain small, and still survive by avoiding confrontation with many of their competitors. However, Geroski (1995) states that both firm size and age are positively correlated with the survival of entrants, meaning that small firms have lower probabilities of survival.

Which theory is then correct? Agarwal and Audretsch (2001) suggest that both can be true, but that each of these statements tends to be particular for a specific phase of the life cycle of an industry, which is then related to the technological intensity of the industry. Therefore, the theory presented by Geroski should hold true in the earlier stages of the life cycle, and for products that are relatively low in technological intensity. On the other hand, Porter's theory should hold true in the more mature phases of the life cycle, and when the product being considered is characterized as high-technology.

Agarwal and Audretsch (2001) suggest that the stage of the product life cycle is a proxy for differences over time in the level of technological intensity since the life cycle is related to differences in the technological regimes. While critical innovations usually take place in the earlier stages of the life cycle, products may have higher or lower levels of overall technological intensity over the entire product and industry life cycles. Agarwal and Audretsch go on to suggest that, when neither the time of entry nor the technological intensity are taken into account, the survival rates for larger firms are significantly higher. However, when the life cycle is taken into account, the results reveal that only for the earlier stages of the industry life cycle the survival likelihood is greater for larger firms. This size advantage disappears in the mature life cycles of the industry, with smaller firms displaying survival rates similar to larger ones, and with the ten-year survival rate being higher. Similarly, the authors found that when the technology level of the industry is considered, firm size bestows a clear advantage in low-tech industries, but this is not true for high-tech ones, with the survival rates of small firms being consistently higher for firms that enter high-tech industries than for those in low-tech. Thus, smaller firms are not at a disadvantage relative to their larger counterparts in high-tech industries in terms of survival.

As such, in general, small entry size is a disadvantage, as many studies presented so far suggest. However, as suggested by Agarwal and Audretsch (2001), small firms entering high-tech industries at later stages of the life cycle have hazard rates comparable to their larger counterparts, with even smaller hazard rates after reaching the age of four. Such findings are in accordance with the particular niche-theory advanced by Porter. Other studies also suggest that high-tech firms may be at an advantage in some scenarios: Tiziana and Alessandro (2011) point out that the likelihood of survival increases from low to high-tech markets and that entering a high-tech market reduces a firm's hazard rate. The authors indicate that smaller firms have a hazard rate similar to their larger counterparts when a high-tech environment is considered. Sarkar et al. (2006) also point out that the new entrants who present the highest survival rates are those entering in high-tech environments, characterised by high levels of investment in innovation. Furthermore, they also reveal that, when small entrants are considered, only a high-tech environment with high levels of innovative activity gives them better chances of survival than those of larger firms.

Audretsch and Mahmood (1994) findings go in accordance with the aforementioned studies, stating that start-up size is important in reducing the hazard rate for new entrants in low and moderate-tech industries, but not in high-tech industries where there is no effect of start-up size. They hypothesize that, in a high-tech environment, initial size and scale considerations do not play a crucial role in the ability to survive, and that rather innovation is the most important factor in such industries.

Summarizing, the investment in innovative activities is often related with an increase in survival prospects (Audretsch, 1995; Christensen, 1997; Gort & Klepper, 1982). Furthermore, innovation is closely related with the industry life cycle: in its early years, technological opportunities for innovation are the highest, but decline as the industry matures. As such, the necessary knowledge companies must have to prosper changes with the industry life cycle (Agarwal & Gort, 2002). Additionally, technological intensity is also crucial to consider, since, the industry's life cycle is related with it (Gort & Klepper, 1982; Nelson & Winter, 1982). The findings in the literature suggest that a high-technological environment leads to technological obsolescence, lowering the survival chances of firms in it (Agarwal & Gort, 2002).

3.3 - The role of exports

Lastly, another important factor that influences the survival of firms in an industry is if they are exporting firms or if they are not. Baldwin and Yan (2011) argue that non-exporters are generally less efficient than exporters, which leads to higher likelihood of failure for the non-exporters. Wagner (1995) suggests that the average firm size is larger for firms who export, indicating that there exists a positive relation between exporting activities and survival probability. Wagner also reports that increases in exporting intensity are positively correlated with total sales growth. Furthermore, Bernard and Wagner (1997) find that exporting firms have better performance attributes than non-exporters, even within the same industry, being larger, more capital-intensive and more productive than non-exporters. The authors hypothesise that increasing exportation intensity promotes faster output and productivity growth, by leading to greater capacity utilization, economies of scale, incentives for technological improvements and increased management efficiency due to competition abroad. Similarly, Bernard and Jensen (1995) suggest that exporters have larger sizes, are more productive, more profitable and are more capital and technology intensive than their non-exporting counterparts.

Exporting can be considered as a form of risk diversification through spread of sales over different markets with different business cycles conditions, or in different phases of product life cycles (Wagner, 1995). If this happens, these different markets may provide a way of substituting sales on a firm's home country by sales abroad, when a negative demand shock affects the home country. Loecker (2007) advances the learning-by-exporting hypothesis: when firms enter export markets, they gain new knowledge and expertise which allows them to improve their efficiency level, and that these positive effects are different according to the destination countries. When firms are exporting to highly developed countries, the management skills and innovation required to achieve success are higher than when exporting to developing countries, which will further improve a firm's productivity.

However, exporting may not always necessarily be the best choice for all firms. In fact, Bernard and Wagner (1997) state that the performance of firms after the start of exporting is no better, and often even worse than that of non-exporters. The authors state that this is especially true over short time horizons, when exporters show lower growth rates for most performance measures. Exporting requires extra costs, such as the possible need to prepare user's manuals in new languages or acquiring knowledge on the important laws of the new markets in which the company is going to be operating in (Wagner, 2012). As such, barriers that prevent easy entry into foreign markets involve the need of high monetary investments, successful innovative capabilities and different exchange rates (Bernard & Jensen, 2004; Correia & Gouveia, 2016).

Firms that were already well adapted in their home market will be able to take advantage of export markets to grow, but only the ability to position themselves to compete and sell abroad is the source of superior characteristics at exporting plants. Therefore, good innovative capabilities are important when it comes to being involved with export markets, since it allows the firms to enhance their capabilities of adaptation. In other words, companies that already possessed superior management and innovative skills than their competitors will be able to overcome the risks associated with starting to invest in exporting activities. On the other hand, less-well adapted firms will have much more difficult barriers to overcome, and the risks related to exporting may make it so that the correct decision is in fact not to export. This suggests the existence of a phenomenon of self-selection related to the decision of starting to export. Wagner (2012) states that the pre-entry differences present substantial evidence in favour of this self-selection hypothesis, with future export starters being more productive than future non-exporters, years before they enter the export market. The author states that, in most cases, only the more productive firms will engage in export activities and will be able to compete in international competitive markets.

Concluding, the literature regarding firm survival and growth has analysed which factors of firm and industry dynamics affect firm success. Firm level, age, current firm size and start-up size have been found to be positively related with firm survival (Audretsch, 1995; Bruderl et al., 1992; Cefis & Marsili, 2006; Dunne & Hughes, 1994; Mata & Portugal, 1994). Besides this, innovators and exporters face lower hazard rates than the ones not involved in innovative activities or exports (Audretsch & Mahmood, 1994; Bernard & Wagner, 1997). Lastly, the literature suggests that high levels of technological intensity are a characteristic that lowers the survivability of firms (Agarwal and Audretsch, 2001; Audretsch & Mahmood, 1994).

4 - Data and Research Methodology

4.1 - Variables

The following variables are our main objects of study, with the goal of describing how the survival and firm duration occurs in the Portuguese manufacturing firms. The choice of variables took into consideration what has been followed by researchers in the area, as explained in the literature review.

- Firm age – firm age at each period of time considered.

- Current firm size – logarithm of the number of people employed at the firm. We use the logarithm, as it allows us to interpret the impact that 1% increase in this variable has on the dependent variable.

- Firm start-up size – logarithm of the number of people employed at firm entry. We use the logarithm, as it allows us to interpret the impact that 1% increase in this variable has on the dependent variable.

- Technological intensity – we use the Eurostat/OECD classification of technological intensity based on NACE Rev.2 codes.[1] Using them, it is possible to ascertain to which technological category each company belongs to, with four categories existing for manufacturing industries: high-technology, medium-high technology, medium-low technology and low-technology. However, in our sample, only a small percentage of firms belong to the categories of medium-high-technology (5.75%), and an even smaller percentage belong to high-technology (0.75%). Analysing them separately would increase the probability of obtaining results that would not be statistically significant, due to such a small sample size. To avoid this, we grouped the firms belonging to high-technology and medium-high technology in a general category called high-tech, and did the same for medium-low technology and low-technology firms, in a category called low-tech.

- Innovation investment – in the case of our study, the innovation investment is analysed by considering the sum of the variables “investment in intangible assets”, “investment in R&D” and “investment in software”.

- Exports – in order to study the firm activity related to exports, we consider the sum of the variables that indicate the sales and services provided by each firm, both to the European community (excluding Portugal) and extra-community markets.

[1] For reference, Table A of the Appendix displays the Eurostat classification.

Regarding innovation, in the literature there are several ways to describe and analyse the data related to this variable. Some researchers made use of databases that had a description of the number of innovations, with total innovation rate being defined as the total number of innovations recorded in the years they were researching, divided by industry employment (Acs & Audretsch, 1988; Audretsch & Mahmood, 1995). Others made use of databases identifying innovators as firms who introduced either a product or a process innovation in the period considered, and non-innovators as those who did not (Cefis & Marsili, 2006). R&D investment has also been used as means of comparing innovation between firms (Cohen & Klepper, 1992; Vivarelli, 2014). Some use the number of patents, trademarks and design applications (Buddelmeyer et al., 2010). As we mentioned, for this dissertation, the innovation investment is analysed by considering the sum of the variables “investment in intangible assets”, “investment in R&D” and “investment in software”. Other variables could have been considered, such as “investment in development projects”. However, all other variables that could relate to investment in innovative activities are either already contemplated in the variable “investment in intangible assets”, or the amount of observations in which the value of investment for those variables is positive is too low to be impactful in our analyses. By considering the sum of the aforementioned variables, we are able to ascertain to some extended how much each firm is investing in innovation, but this procedure is somewhat limited. Since we are not considering any direct measure of innovation investment, some factors such as the number of patents, trademarks or number of innovations recorded are not being contemplated. This limitation is due to the characteristics of our dataset, and should be considered when evaluating the results regarding the impact of innovation on firm survival.

For our analyses, we distinguish between innovators and non-innovators. In order to implement this distinction, we first calculate a sliding window mean, with a time span of three years, for the innovation investment of each firm. This innovation investment is calculated as the sum between the investment in intangible assets, R&D and software, divided by the volume of sales of each firm. By dividing this investment by the volume of sales, we account for the fact that firms with higher volume of sales will probably have larger sums of money to invest. As such this is meant to help solve this issue of scale, by considering that the relevant information is this ratio, and not the absolute value of investment. We then calculated the mean of investment in innovation for each of the 28 technological categories to which manufacturing firms can belong according to the NACE Rev.2 codes at the 2-digit level. Lastly, we consider that a firm is an innovator for each period, if their three-year period sliding window mean of innovation investment is larger than the average innovation investment of the technological category to which they belong. This way, we are comparing each firm only with firms with similar characteristics as their own, making for a fairer comparison.

We decided to follow the aforementioned procedure as it allows to better analyse some particular scenarios that may occur in our dataset: The impact on survival of a firm that invests a large sum in innovation in their first year of activity and then never invests again in it can surely be different than that of a firm who invests moderate amounts in each year of activity. If we were to consider a regular mean, and not a sliding window mean, such scenarios would not be contemplated.

By following this distinction, we can no longer state that a firm is simply an innovator or a non-innovator. In fact, firms will be innovators or non-innovators at each year of their activity that is present in our sample, and this status may change for each of their observations. Therefore, it is important to note that, from here on, when we refer to firms as innovators or non-innovators, we mean for each period of their activity, and not as a necessarily steady characteristic those firms have.

Regarding exports, we distinguish between exporters and non-exporters, following a similar logic to the one applied for the case of innovators and non-innovators. We also consider a three-year sliding window mean of the value of exports each firm has and compare, for each firm, the ratio of exports by volume of sales to the average value of exports of the technological category to which each firm belongs. For each observation, if the former is larger than the latter, a firm is considered to be an exporter. Due to this, as for the case of innovators, it is not correct to define a firm as an exporter or a non-exporter, but to rather say that a firm will be an exporter or not, at each year of their activity that is present in our dataset, and that this status may change for each of their observations. As such, the same principle as for innovators is applied here, and, from here on, when we refer to firms as exporters or non-exporters, we mean for each period of their activity, and not as a necessarily steady characteristic those firms have.

4.2 - Research hypotheses

Taking into account the literature review presented in Chapter 3, in this section we present our research hypotheses regarding firm survival and the role of technological intensity and innovation.

The first thing that becomes clear after understanding the problem at hand is that many factors influence the survival and growth of firms in an industry. Besides this, the relationship between these factors is not always completely clear, as different studies arrive to different conclusions. This lack of consensus, however, is to be expected, due to the different characteristics that different industries present, which are related to the way in which the dynamics involved affect the survival of firms. Even though the problem has several variables that are interconnected and relevant, some stand out for their importance, and for the extensive study that they have been put through. Such variables, and the way they impact the firms in the industry, will be the focus of this dissertation.

First, the main topic of this dissertation is to understand how different degrees of technological intensity affect firm survival. A high level of technological intensity is often viewed as an industry characteristic that lowers the survival probabilities of firms in it, since it is related with higher rates of obsolescence of older technologies, lowering the survival probabilities of new firms and incumbents. As technological uncertainty rises, the probability that a firm will be able to produce a viable and desirable product will decrease, along with their chances of survival (Audretsch & Mahmood, 1994). As such, we test our first hypothesis:

H1: Firms in high-tech industries face higher hazard rates than in low-tech ones.

Figure 1 presents the non-parametric survival rates of high-tech and low-tech firms. It suggests that, starting from the third year of activity, high-tech firms present higher survival rates than low-tech ones, which clearly is the opposite scenario to the one described by H1. Even though this preliminary analysis does not allow us to draw definitive conclusions regarding this problem, the more in-depth analysis we perform in Chapter 5 further clarifies the characteristics of the relationship between survival and technological intensity.

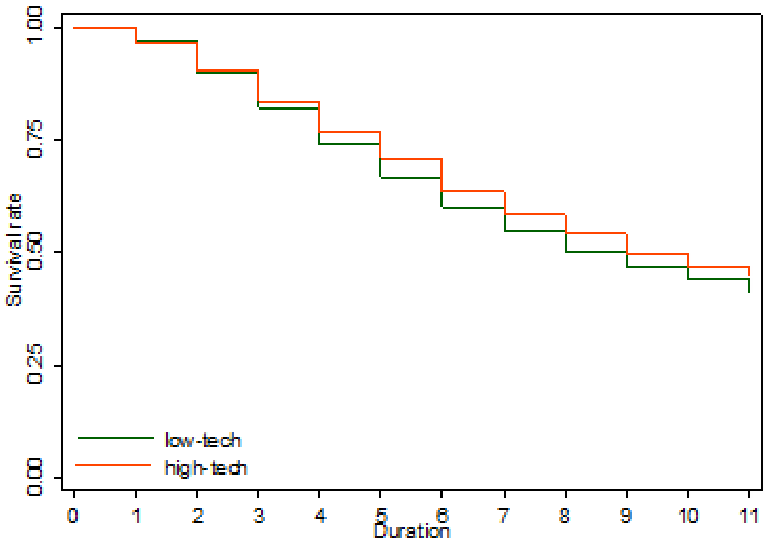

Figure 1 - Kaplan-Meyer survival estimate by technological intensity

Even though small firms are often associated with larger hazard rates than their larger counterparts (Audretsch et al., 2006; Cefis & Marsili, 2006; Dunne & Hughes, 1994), in technologically intensive industries, small firms face similar, or even smaller hazard rates when compared to their larger counterparts (Agarwal & Audretsch, 2001). This can be explained by the fact that small firms co-exist with large firms in the mature phase of the life cycle of an industry (characterized by routinized technological regimes), allowing them to occupy strategic niches that are largely unexplored by large firms, boosting their survival chances (Porter, 1979). As such, for our second hypothesis, we specify this particular scenario:

H2: Small firms face lower hazard rates in high-tech industries than in low-tech ones.

High-tech environments are characterized by frequent product innovations, which will be associated with greater uncertainty, making it more difficult to produce viable and desirable products (Audrestch & Mahmood, 1994). Moreover, high degrees of technological change lead to higher rates of technological obsolescence (Agarwal & Gort, 2002). It is through successful innovation that firms are able to adapt to a rapidly changing environment. Due to this, innovation is a crucial factor in a high-tech environment, even more so than in a low-tech one. Taking this into consideration, we formulate the following hypothesis:

H3: Firms benefit more from being innovators in high-tech industries than in low-tech ones.

One characteristic of firm dynamics that was studied deeply is the age of firms, and its relationship with survival. Small and young firms present higher failure rates in most industries (Cefis & Marsili, 2006; Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Hall, 1987). This phenomenon, discussed as the "liability of newness", appears to be the most common, even though other phenomena such as the "liability of adolescence" (Brüderl & Schüssler, 1990; Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991) and "liability of senescence" (Hannan, 1998) have also been described. As such, several hypotheses have been placed that relate the age of firms with their chances of survival. Many firms that enter a market are not able to adapt to the adversities that they end up facing and are forced to leave soon after entry. In fact, a study undertaken in the Portuguese market in 1983 affirms that about half of the firms fail after only four years of activity (Mata & Portugal, 1994). The firms that adapt and survive will likely grow, and will have larger chances of survival. Such results are consistent with the learning model presented by Jovanovic (1982). Taking this into account, our fourth hypothesis is as follows:

H4: Older firms face lower hazard rates than younger ones.

Another topic that was studied deeply is the relationship between the size of the firms and their survival probability. Many studies have indicated that firm size is positively related to the chances of survival (Audretsch et al., 2006; Cefis & Marsili, 2006; Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Hall, 1987). Studies on the Portuguese economy (Mata & Portugal, 1994; Mata et al., 1995) seem to support this idea as well. Following this, we advance our fifth hypothesis:

H5: Larger firms face lower hazard rates than smaller ones.

Figures 2 and 3 displays the survival rates, using a non-parametric approach, for three different firm size classes, for high-tech and low-tech firms, respectively. As we can see, the results reveal that firm survival and firm size are positively correlated, for both levels of technological intensity. The firms that present the largest survival rate are the ones with six or more employees, while the ones who are least likely to survive are the firms with only one employee.

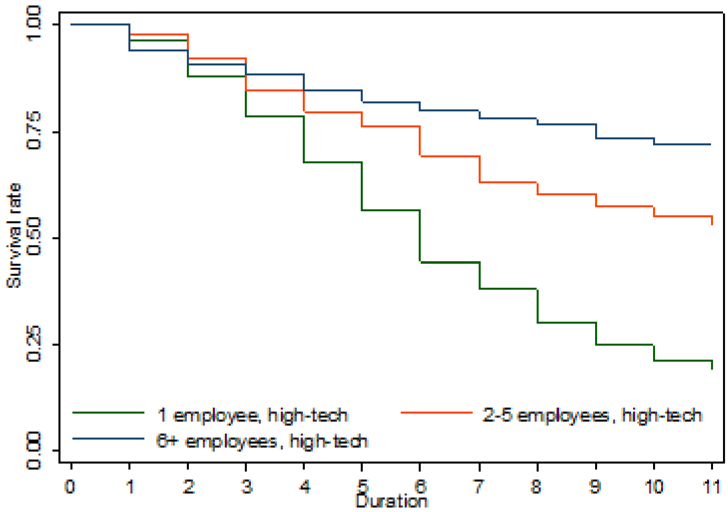

Figure 2 - Kaplan-Meyer survival estimate by current size class, for high-tech firms

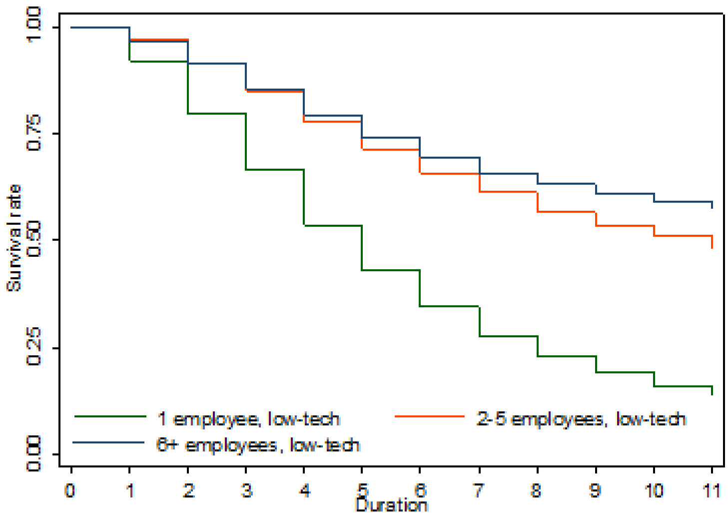

Figure 3 - Kaplan-Meyer survival estimate by current size class, for low-tech firms

A special deal of attention has been paid to the importance of the firm size at the time of entry. Firms with smaller start-up sizes are expected to face higher probabilities of failure, surviving for shorter periods of time (Bruderl et al., 1992; Mata & Portugal ,1994). When firms enter with a larger scale, their initial endowments are ample enough to allow them to survive for longer periods of time (Fichman & Levinthal, 1991). Besides this, the cost disadvantage associated with the gap between a firm's level of output and the minimum efficient scale level of output is larger for smaller firms, which means that firms that start at a smaller scale face higher hazard rates (Esteve-Pérez & Mañez-Castillejo, 2008). Considering this, we state the following hypothesis:

H6: Firms with larger start-up sizes face lower hazard rates than those with smaller start-up sizes.

The non-parametric survival rates by start-up size class and technological intensity are shown below, with Figure 4 displaying the results for high-tech firms, and Figure 5 for low-tech ones. Figures 4 and 5 show that the firms that present the lowest survival rates are the ones that start with only one employee. However, Figure 5 also suggests that the firms that present the higher survival rates are in fact low-tech firms with between two to five employees, being followed by low-tech firms with six or more employees. Given this, Figure 5 seems to suggest that starting too big may be in fact a disadvantage for low-tech firms.

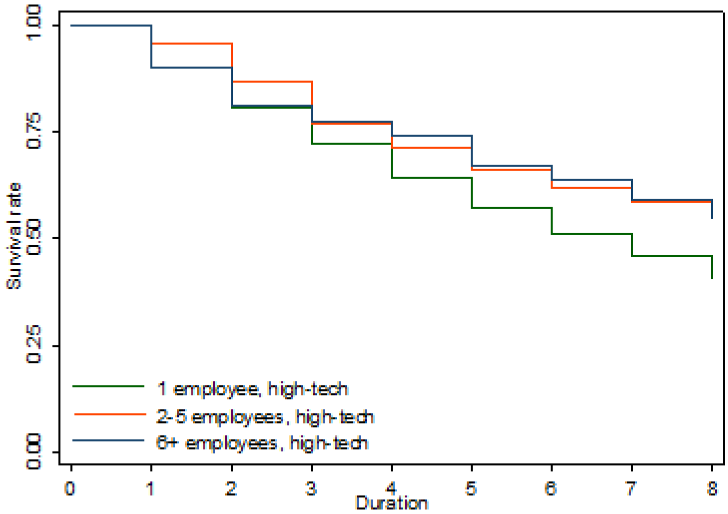

Figure 4 - Kaplan-Meyer survival estimate by start-up size class, for high-tech firms

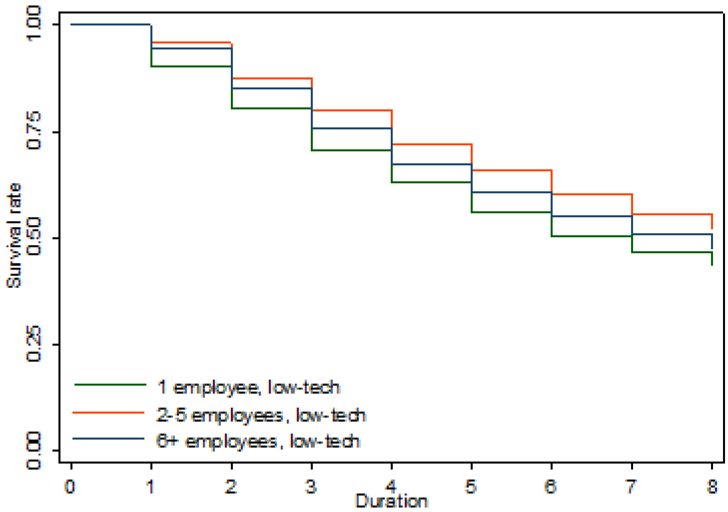

Figure 5 - Kaplan-Meyer survival estimate by start-up size class, for low-tech firms

Successful innovative activities allow firms to adapt to changes in the environment, and to better respond to the changing needs of their customers. As such, innovation strongly determines the survival of both new firms and incumbents (Audretsch, 1995; Cefis & Marsili, 2006). Innovation has been studied deeply, and the general consensus is that firms that successfully innovate face lower hazard rates than those who do not. This leads to the following hypothesis:

H7: Innovators face lower hazard rates than non-innovators.

Figures 6 and 7 present the non-parametric firm survival rate for innovators and for non-innovators. Figure 6 presents the results regarding high-tech firms, while Figure 7 presents the results regarding low-tech firms. As shown, firms that do invest in innovative activities tend to have higher survival rates than those that do not, for both levels of technological intensity, which goes in accordance with what is described in the literature, giving motivation to H7.

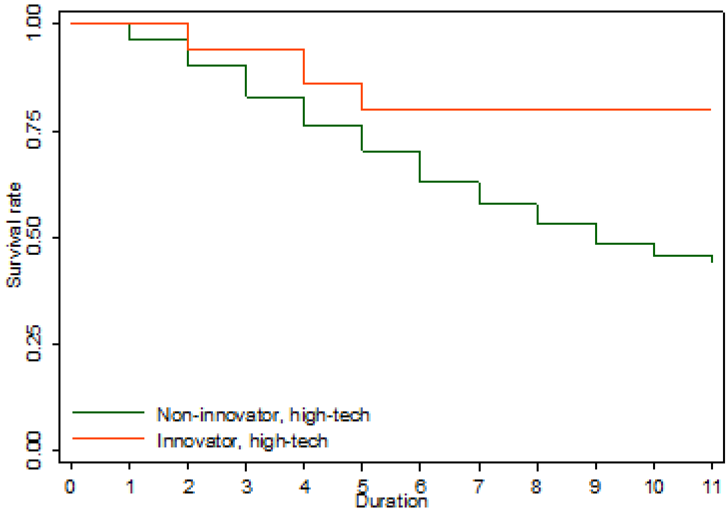

Figure 6 - Kaplan-Meyer survival estimate for innovators and non-innovators, for high-tech firms

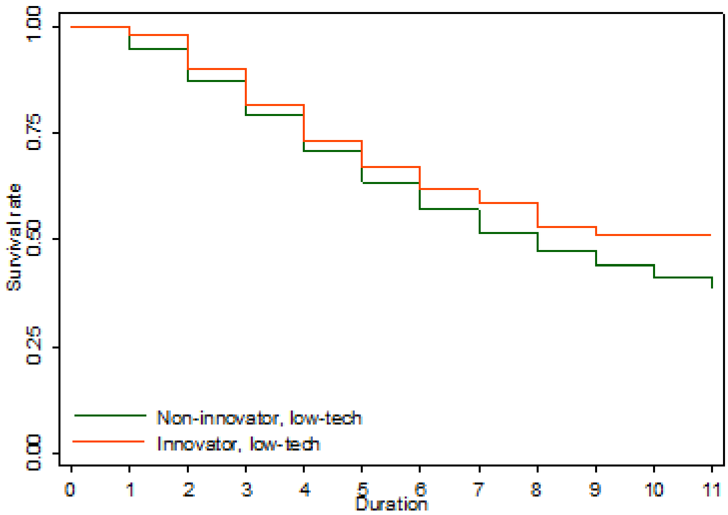

Figure 7 - Kaplan-Meyer survival estimate for innovators and non-innovators, for low-tech firms

Lastly, when considering the role of exports, firms that are able to successfully export were found to usually be more productive than their non-exporting counterparts, presenting larger sizes, being more profitable and more capital and technology intensive than their non-exporting counterparts (Baldwin &

Yan, 2011; Bernard & Wagner, 1997; Wagner, 1995). Exporters also boast other advantages such as being able to soften the impact of negative demand shocks in their home markets, by being active in markets abroad (Bernard & Wagner, 1997). Additionally, since exporting firms spread their sales over different foreign markets and countries that often have different business cycle conditions than their home market, they become able to diversify their risks (Wagner, 1995). Taking the aforementioned advantages into account, we formulate our final hypothesis:

H8: Exporters face lower hazard rates than non-exporters.

The non-parametric survival rates are presented in Figures 8 and 9, regarding the case of both exporting and non-exporting firms. Figure 8 presents the results regarding high-tech firms, while Figure 9 presents the results regarding low-tech firms. The results suggest that there exists a difference in survival probability between exporters and non-exporters, with the prior having larger chances of surviving than the latter, for both high-tech and low-tech firms.

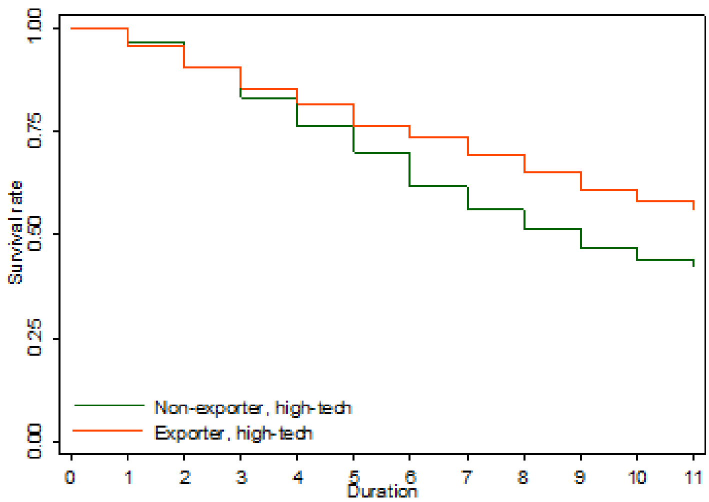

Figure 8 - Kaplan-Meyer survival estimate for exporters and non-exporters, for high-tech firms

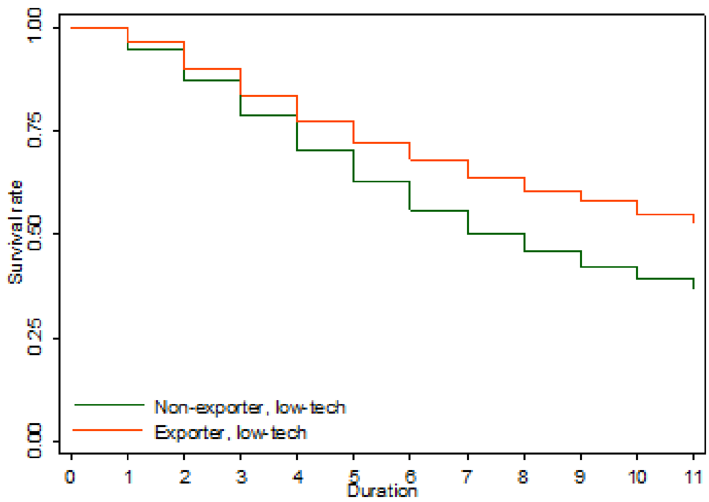

Figure 9 - Kaplan-Meyer survival estimate for exporters and non-exporters, for low-tech firms

4.3 - Survival analysis and hazard model

Survival analysis is a type of statistical method that helps describe the occurrence and timing of events. This analysis involves the estimation of regression models where the independent variable is a measure of time or rate of an occurrence. Survival analysis is particularly useful as it gives the researcher the ability to handle right censoring, which occurs when some of the individuals in the sample do not experience the occurrence of the events we are interested in studying, which implies that an event time cannot be measured. Due to this, conventional statistical methods (like ordinary least squares regression) are not good choices for duration analysis, as they do not account properly for right-censoring, producing biased and inconsistent estimates. In our case, we are interested in studying firm duration and firm failure, in which information with respect to duration is typically incomplete, since at the time of the survey there persists a number of cases that did not fail, making it right-censored. Therefore, the right choice is to employ models specifically designed to take this problem into account, which leads us to the study of survival analysis and hazard models (Allison, 1984; Jenkins, 2005). We apply these models to study the instantaneous probability of a firm leaving the market we are studying, which is commonly called the hazard rate.

The hazard model gives a risk of failure for each point in time, i.e., the conditional probability that a firm will exit the market in the next time interval, conditional on the firm having survived to the start of the time interval that is being studied. By defining the hazard rate as *λ(t)*, we can write the hazard function as:

$$\lambda(t) = lim_{\Delta t \to 0^+} \frac{P(\, t \leq T \leq t + \Delta t \, | T \geq t)}{\Delta t} = \frac{f(t)}{S(t)}, \tag{1}$$

where *T* is a random variable representing failure time, *f(t)* is the probability density function of the event occurring and *S(t)* is the survival function, given by:

$$S(t) = P(T \geq t), \tag{2}$$

Mata and Portugal (1994) affirm that the notion of duration dependence is associated with the hazard rate. If the duration dependence is positive, the hazard rate will increase with time, which, in our model means that $d\lambda(t)/dt > 0$. On the other hand, if a negative duration dependence occurs, the hazard rate will decrease with time, which, in our model means that $d\lambda(t)/dt < 0$ (Mata & Portugal, 1994).

What we are interested now is in investigating the impact of the independent variables on the probability of firm failure. We can do this by implementing a multivariate model of the duration of firms, such as the proportional hazards model (Cox, 1972), which is defined as follows:

$$\ln\lambda(t) = \ln\lambda_0(t) + X\beta, \tag{3}$$

The parameters of the equation are the following: $\lambda_0(t)$ represents the baseline function, which is dependent on time, but not on ***X,*** summarizing the patterns of "duration dependence". ***X*** is a vector of exploratory variables, not dependent on *t*, and ***β*** is a vector of the parameters we want to estimate (Mata & Portugal, 1994). It is important to note that the baseline hazard is equal to the hazard function when ***X*** = ***0***, which means that the effect of the independent variables is to act multiplicatively on $\lambda_0(t)$. Hence the name of proportional hazards.

In order to fit proportional hazards models, there are three approaches that can be followed: parametric, semi-parametric, and non-parametric ones.

- Parametric approaches require the researcher to make assumptions on the shape of the baseline hazard in order to estimate the parameters of the independent variables. However, if the choice for such is not proper, it can lead to unreliable estimates (Heckman & Singer, 1984; Jenkins, 2005; Mata & Portugal, 1994). Parametric models assume particular families of probability distributions, with common ones being exponential, Weibull, Gompertz, lognormal, log-logistic, or gamma (Allison, 1984).

- Semi-parametric approaches, with the most common one being the Cox (1972) model, allow the researcher not to make assumptions about the probability distribution. One can estimate the relationship between the hazard rate and explanatory variables without having to make any assumptions about the shape of the baseline hazard function (Jenkins, 2005).

- The non-parametric approaches can be useful, as they allow for relaxed assumptions that enable robust estimation, since these approaches do not demand researchers to specify the shape of the baseline hazard function. However, when using non-parametric methods, researchers cannot study how the independent variables impact the survival chances (Jenkins, 2005).

Some advantages of parametric representations of the duration distribution are that, when these are properly specified, lead to more efficient estimators, creating fewer computational difficulties, making it easier to perform a probabilistic analysis of the duration dependence phenomenon (Mata & Portugal, 1994). One common model to achieve this is the Weibull model, where the baseline hazard function is defined as:

$$\lambda_0(t) = y\rho(\rho t)^{y-1}, \tag{4}$$

The γ parameter in this equation implies the following scenarios: for $\gamma > 1$, there is a positive duration dependence (monotonically increasing); for $\gamma < 1$, there is a negative duration dependence (monotonically decreasing); for $\gamma = 1$, an exponential hazard function (constant hazard rates) is implied.

As explained, making assumptions regarding the shape of the baseline hazard may be a disadvantage, and that is why the Cox model is frequently used. By not having to fit a baseline hazard function, the model allows derivation of estimates of the slope coefficients within the vector $\boldsymbol{\beta}$ from a proportional hazards model, but places no restrictions on the shape of the baseline hazard. However, there is a tradeoff between making an assumption on the distribution of time to failure and the ability to estimate the role of the duration dependence on survival probabilities, which is not possible in a semi-parametric approach such as Cox. Since the impact of firm age on survival (the aforementioned role of duration dependence) is exactly one of the hypotheses that are to be studied in this dissertation, the role of duration dependence is crucial, making it so that the Cox model is not ideal in our scenario.

A model that fits the characteristics we desire for our study is the piecewise-constant exponential model. This parametric continuous-time duration model requires that we subdivide the time of our analysis into intervals. We consider that the hazard is assumed constant within this pre-specified survival time intervals but that the constants may differ for different intervals. This assumption offers some flexibility, making weaker assumptions on the overall shape of the baseline hazard, minimizing the disadvantages inherent to this.

Although this piecewise-constant exponential model is the one that better fits our problem, we also perform tests with the Weibull and Cox model for robustness sake. If our model is robust, the results using the different models should be similar, which would serve as a guarantee that the outcome of our models is trustworthy.

4.4 - Dataset: Sistema de contas integradas de empresas

4.4.1 - SCIE description

In order to analyse firm survival, we use the Integrated Business Accounts System *(Sistema de Contas Integradas de Empresas* – SCIE) dataset.

According to the Portuguese Institute of Statistics, SCIE's main objective is to characterize the economic and financial behaviour of Portuguese firms, through a set of variables deemed relevant to the business sector, and by using financial ratios commonly used in business financial analysis. The dataset also aims to characterize the dynamics of firms, with special relevance to their creation and death and the variation of the number of people working on them, by including demographic features of firms.

For each year, the population of SCIE is composed by the firms (societies, sole proprietors and independent workers) that have production activity of goods and/or services during that period, in the whole country. From the dataset are excluded financial and insurance companies, as well as companies that are not market-oriented, namely units of central and local public administration and assortments of associative activities. The scope of the economic activity considers the firms classified in sections from A to S of the statistical classification of economic activities in the European Community — NACE Rev. 2.

4.4.2 - Sample construction

Following the scope of this dissertation, we only consider Portuguese manufacturing firms, with the data available belonging to the years of 2007 to 2015. While our analysis time frame begins in 2007, we follow firms that were born in 2004 and after, though these observations are left-truncated. This delay entry means that some firms were already at risk of closure by the time our analysis begins (in our dissertation, we consider that firm closure occurs when there is a registered firm death in our dataset). From a different perspective, it means that some of the firms born in 2004 (or later) might not have survived until our analysis began, leading to a sample that is composed of survivors. Fortunately, the model we use easily accounts for the delayed entry issue.

Having made this selection, from the resulting sample, we only considered the observations that correspond to “societies”. The data related to individual firm owners was excluded, as they commonly have a different behaviour from regular firms and may not be focused on making profit. Further, we excluded all the observations in the sample that did not have the year of birth of the firm, as the year of birth is necessary to perform an analysis of firm survival. We also excluded the observations for the year 2015, as we do not have any information about firm closures in this year, and information regarding closures is also necessary to analyse firm survival (15.25% of the observations were excluded due to this restriction). Furthermore, we excluded firms for which the total number of sales and services provided is zero for all of the years they were present in the dataset, since they were inactive for the whole period of our study (3.98% of the observations were excluded due to this restriction). For the particular case of firms that have their death documented in the dataset, but that re-enter the dataset once more on a later date, we discarded all the entries after the first death, so as to simplify the interpretation of the results (0.07% of the observations were dropped due to this restriction). Lastly, we only consider firms for which their level of technological intensity never changes (0.17% of the observations were dropped due to this restriction). We do this since we are trying to test how the variables differently affect survival for the cases of low-tech and high-tech firms. Firms that switch from low-tech to high-tech environments, or vice-versa, would be subject to vastly different environmental pressures in the periods of their lives before and after switching, making the study of the influence of the variables more difficult. Having applied all the aforementioned restrictions, we are left with a sample with 93317 observations and 22198 firms.

4.5 - Characteristics of the sample

In this section we discuss the sample that was constructed following the procedure described (see section 4.4.2). We must emphasise that for some analyses, we impose further restrictions on the dataset than the ones we already mentioned, as needed for each model that is being tested. Whenever we apply any of these restrictions, we provide an explanation regarding the reasons behind it, justifying the needs for the further decrease in the number of observations considered.

In the following sections, we analyse the variables that were previously presented. We aim to ascertain their general characteristics, and to start analysing how the survival chances of firms are influenced by each variable. Doing this, we may start to relate the results with the hypotheses we previously constructed.

It is important to mention, however, that this analysis is still a preliminary one, as the variables are analysed individually. As such, in this section, we are not considering the effects that the other variables have on each individual variable, and no other controls are yet being used. The more in-depth procedure is presented in Chapter 5, in which we present the results of the econometric models, discussing them more attentively.

4.5.1 - Summary statistics

In this section we present the summary statistics for the variables that we analyse. It is important to mention that, for the case of start-up size, we do not know the start-up size of firms which year of birth happened before 2007, which meant that these were discarded from this analysis. As such, in the resulting sample, the number of firms is of 17962.

As presented in Table 1, for the variables age, firm size and start-up size, this analysis includes their division into classes, so as to simplify the interpretation of the results. The choice on how to divide the variables in different classes was made by considering which divisions better correspond to the characteristics of our sample, and not following directly any method described in the literature. In the following sections we analyse all the variables and explain the reasoning behind the classes created.

For the cases of the summary statistics and when we analyse the impact of innovation and exports, we only take into account the last observation of each firm. This was done because, if we were to consider all observations that each firm has in the sample, the results would be biased, since firms that have more observations in the sample (i.e. older firms) would contribute more to this average.

Table 1 - Summary statistics for the main variables

	All firms	High-tech firms	Low-tech firms
Age (years)	3.985 (2.493)	4.099 (2.532)	3.977 (2.489)
Age: 1 year	0.178 (0.382)	0.168 (0.374)	0.178 (0.383)
Age: 2 to 4 years	0.457 (0.498)	0.448 (0.497)	0.458 (0.498)
Age: 5 to 6 years	0.191 (0.394)	0.198 (0.398)	0.191 (0.393)
Age: 7 or more years	0.174 (0.379)	0.186 (0.389)	0.173 (0.378)
Firm size (employees)	7.446 (17.74)	9.644 (34.15)	7.387 (15.912)
Firm size: 1 employee	0.271 (0.444)	0.358 (0.479)	0.264 (0.441)
Firm size: 2 to 5 employees	0.395 (0.489)	0.360 (0.479)	0.398 (0.489)
Firm size: 6 or more employees	0.334 (0.472)	0.282 (0.450)	0.338 (0.473)
Start-up size (employees at time of birth)*	4.038 (7.274)	3.042 (6.601)	4.116 (7.286)
Start-up size: 1 employee*	0.433 (0.496)	0.557 (0.497)	0.424 (0.494)
Start-up size: 2 to 5 employ-ees*	0.371 (0.483)	0.316 (0.465)	0.376 (0.484)
Start-up size: 6 or more em-ployees*	0.196 (0.397)	0.127 (0.332)	0.200 (0.400)
Innovator (binary value)	0.052 (0.222)	0.044 (0.204)	0.053 (0.223)
Exporter (binary value)	0.124 (0.330)	0.167 (0.373)	0.121 (0.327)
High-tech firm	0.065 (0.250)	-	-
Low-tech firm	0.935 (0.250)	-	-
Region: Norte	0.563 (0.497)	0.399 (0.322)	0.574 (0.481)
Region: Centro	0.192 (0,401)	0.258 (0.137)	0.187 (0.387)
Region: Lisbon	0.161 (0.364)	0.257 (0.398)	0.155 (0.378)
Region: Alentejo and Algarve	0.062 (0.209)	0.071 (0.208)	0.061 (0.218)
Region: Azores and Madeira	0.022 (0.216)	0.015 (0.211)	0.023 (0.244)
Number of observations	93317	6269	87048
Number of firms	22198	1443	20755
Number of closures	7725	478	7247
Proportion of closures (%)	34.80	33.13	34.92

Statistics computed using only the last observation of each firm. For categorical variables the mean represents the proportion of firms in each category. Standard errors presented in brackets.

*For statistics considering start-up size, for all firms the number of observations is of 63483 and the number of firms is of 17962; for high-tech firms the number of observations is of 4324 and the number of firms is of 1227; for low-tech firms the number of observations is of 59159 and the number of firms is of 16735

4.5.2 - Age

Age is one of the main factors that affects the survival chances of firms in an industry. As discussed in the literature, age is positively related with a firm's survival probability (Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Hall, 1987). As such, it is one of the relevant determinants of firm dynamics to be considered in our analysis. The life duration is calculated as the number of years in which firms were observed in the sample, by subtracting the year of each observation from the year of birth of each firm. It is important to note that the data present in our sample is right censored, since death was only observed for 34.80% of the total number of firms present in our sample.

The average life duration for firms present in the dataset is of 3.985 years, which goes to show that, as according to Mata and Portugal (1994), the majority of firms die young. For the following analysis, we calculate the percentage of closures for each age class. The results are shown in Table 2:

Table 2 - Percentages of closures by age class

	1 year	2 to 4 years	5 to 6 years	7 or more years	Count
Surviving firms	76.18%	56.72%	56.14%	78.86%	14473
Closures	23.82%	43.28%	43.86%	21.14%	7725
Count	2901	9227	4015	6055	22198

As presented in Table 2, the firms that present the largest probability of survival are those with seven or more years (78.86%), which goes in accordance with the findings in the literature (Dunne & Hughes, 1994; Evans, 1987a; Evans, 1987b; Hall, 1987) that state that older firms are more resilient, and face lower hazard rates than their younger counterparts. However, the data indicate that firms that are one year old have higher survival percentages (76.18%) than those that are between two and four years old (56.72%) and those that are between five and six years old (56.14%). These findings indicate that, when age is considered, firms tend to leave the market mostly after some initial years of activity, following a hypothesis called the "liability of adolescence". This may be explained by the fact that, during the first years of activity, firms still have resources that were gathered at the time of birth, and that are being used up. However, after these initial resources run dry, if the firms do not find success in the market, the best course of action may be to exit the market, leading to higher closure rates on the years immediately after the first few of activity (Brüderl & Schüssler, 1990; Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991).

The fact that the "liability of adolescence" is the hypothesis that better seems to describe our data was the reason why we decided to divide the sample of firms into four age classes (1 year, 2 to 4 years, 5 to 6 years, 7 or more years). Since the survival rates start going up once more on the seventh year of activity, dividing the data into these classes allows for a better visualization and analysis of the impact of age on firm survival. The fact that it takes until the seven-year mark for the survival percentage of firms to start growing once more is something uncommon in the literature, but it still follows the same principle of the "liability of adolescence". The econometric analyses that we present on Chapter 5 sheds more light on this subject.

4.5.3 - Firm size

The likelihood of survival of a firm is also influenced by its size, with larger sizes being related with higher survival chances (Bruderl et al., 1992; Mata & Portugal, 1994). In this section we evaluate the characteristics of firm size in the industry studied. The size of each firm is considered to be the number of employees a firm has, for each observed year of activity.

According to Mata and Portugal (1994), the Portuguese manufacturing industry in the eighties was characterized by having a large number of firms of small size. The average number of employees in the firms that compose our sample is of 7.446, which indicates that the statement by Mata and Portugal still holds true, with firms still being, on average, of small size.

Figure 10 presents the data on our analysis regarding the size of the firms in our sample, both in terms of number of firms per size class, and by employment per size class.

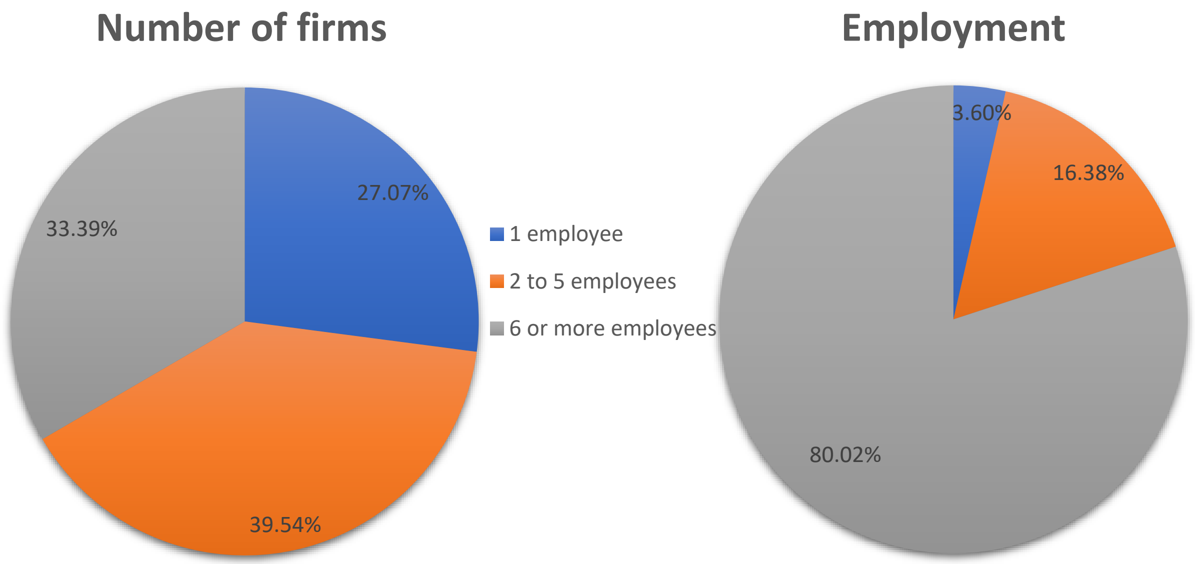

Figure 10 - Number of firms (%) and employment (%) by current size class

The size classes constructed are of 1 employee, 2 to 5 employees and 6 or more employees. As Figure 10 indicates, the majority of firms are clustered into the lower size range. In fact, 27.07% of firms have only one employee, with 39.54% of firms having between two to five employees. In other words, 66.61% of firms have 5 or less employees. This goes to show that only a small percentage of firms are of big size – in fact, only 13.93% of firms have more than 10 employees, and only 1.43% have 50 employees and over. Considering this, we constructed the firm size classes centred around small values of firm size, since they better represent the sample we are studying.

On the other hand, when it comes to employment, we can see that the opposite occurs, with the largest percentage of employees (80.02%) working on firms with six or more employees, and only 3.60% working on firms with only one employee. This indicates that the majority of employees are working on the firms of larger size, even if their quantity is smaller when compared to smaller firms.

There are many reasons for why firms in the sample are of small size. In fact, many firms die young, before they have an opportunity to grow, as proposed by Jovanovic (1982). The author states that firms will learn about their efficiency by working in an industry. The firms who are efficient, survive and grow, while the ones that do not succeed in the industry will leave, while still at a small size. Besides this, there have been pointed out some behavioural advantages that small firms may have, such as being able to place themselves in niche markets, avoiding conflict with incumbents, boosting their survival chances (Caves & Porter, 1977; Porter, 1979).

However, as discussed, large firms have some inherent advantages when competing in an industry. They have more resource availability (Mata & Portugal, 1994) and the cost disadvantage associated with the gap between a firm's level of output and the MES level of output is smaller for larger firms, leading to smaller hazard rates (Esteve-Pérez & Mañez-Castillejo, 2008).

As was done for the case of the life duration of firms, we calculate the percentage of closures for each size class. The results are presented in Table 3:

Table 3 - Percentage of closures by current size class

	1 employee	2 to 5 employees	6 or more employees	Count
Surviving firms	53.56%	69.75%	72.25%	14473
Closures	46.44%	30.25%	27.75%	7725
Count	7278	8196	6724	22198

As we can see, the firms that present the lower survival percentages are those that have only one employee (53.56%), with the ones that have the highest survival percentages being the ones that are composed of six or more employees (72.25%). These findings go in accordance with the proposal that firm size is indeed proportional to survival chances.

4.5.4 - Start-up size

Just as for the case of firm size, start-up size also impacts firm survival. The relation is similar as in the previous case, with larger start-up sizes being related with higher chances of survival (Bruderl et al., 1992; Mata & Portugal, 1994). In this section we evaluate the characteristics of the start-up size in the industry studied.

Portuguese manufacturing firms start with an average of 4.038 employees, which suggests that the statements by Mata and Portugal (1994) still hold true, with firms still starting small. This value is smaller than that for the average firm size (7.446 employees), which reveals that firms are nonetheless growing when compared to the initial period of their lives.

Following the same procedure as was done for the firm size, we divide the whole sample of firms into the same start-up size classes. The results are presented in Figure 11:

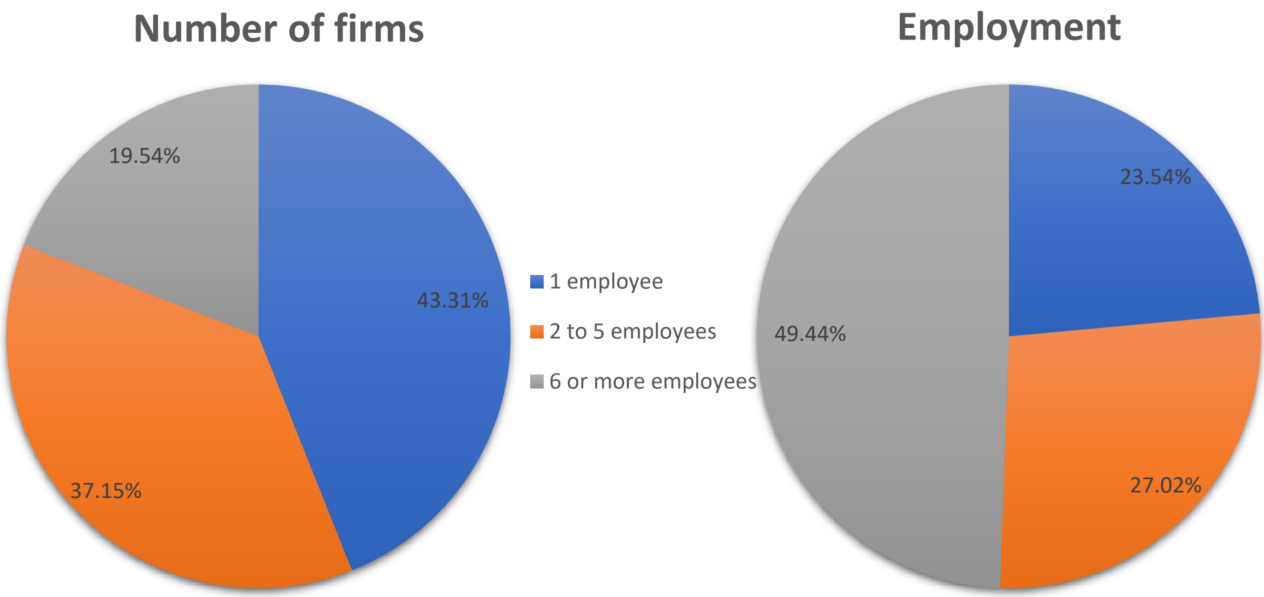

Figure 11 - Number of firms (%) and employment (%) by start-up size class

As shown, the fact that the sample has an abundance of small firms is even clearer when evaluating start-up size. In fact, 43.31% of firms start with only one employee, with only 19.54% starting with six or more employees, which means that only a small portion starts already at a size comparable to the average incumbent. This could create a disadvantageous situation for the majority of firms, since firms that start at larger sizes have higher initial endowments, which allows them to have higher average survival chances in the beginning of their lives than their smaller counterparts (Fichman & Levinthal, 1991).

Following the same logic applied for the case of firm size, we calculate the firm closure by start-up size dimension class. However, for the case of start-up size, we had to exclude all the firms that were born prior to 2007, as we do not have data about their size at the moment of birth, which lead to a decrease in the number of observations.

Table 4 - Percentage of closures by firm start-up size class

	1 employee	2 to 5 employees	6 or more employees	Count
Surviving firms	65.34%	71.83%	66.19%	12173
Closures	34.66%	28.17%	33.81%	5789
Count	8396	6301	3265	17962

Table 4 suggests that the firms which present the lowest survival percentages are the ones that start with only one employee, which goes in accordance with what is expected (Bruderl et al., 1992; Esteve-Pérez & Mañez-Castillejo, 2008; Mata & Portugal, 1994). However, firms that start with six or more employees present survival percentages of 66.19%, lower than those that have start-up sizes between two to five employees (71.83%). This may suggest that starting too big may be, in fact, not optimal for a company.

4.5.5 - Technological intensity

The technological environment that surrounds firms has an impact on their survival. In order to understand how the overall technological environment in the Portuguese manufacturing industry is composed, we calculate the percentages of both high-tech and low-tech firms, as well as the data regarding employment for both technological intensities. The results are shown in Figure 12:

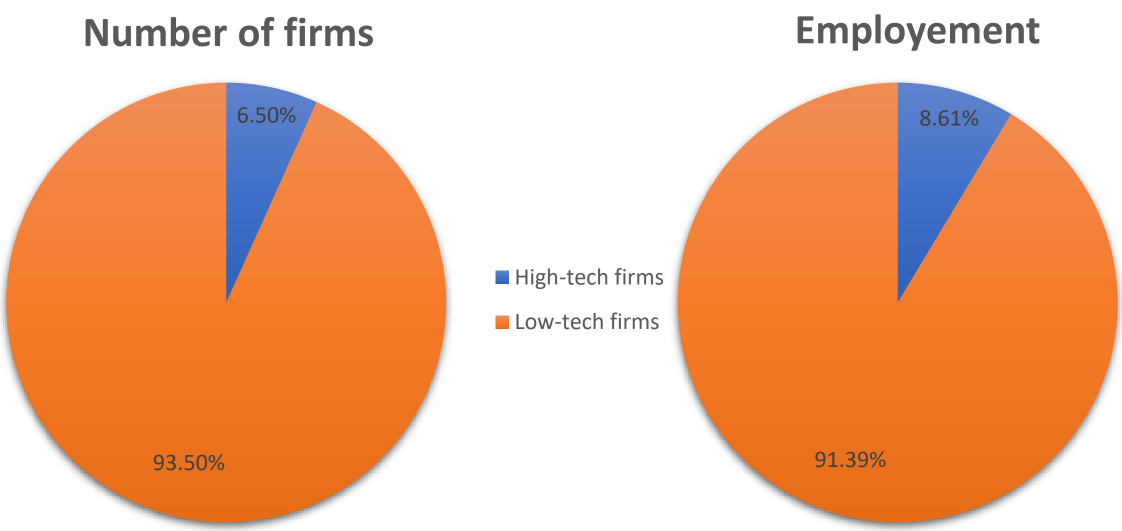

Figure 12 - Number of firms (%) and employment (%) by technological intensity

As we can see, the majority of the Portuguese manufacturing industry is composed of low-tech firms, with 93.50% of them being low-tech. Firms in low-tech and high-tech environments face different conditions that will affect their survival chances differently. Audretsch and Mahmood (1994) affirm that high levels of technological intensity may lower the survival chances of firms, as these conditions are related to technological uncertainty. The probability that a firm will be able to produce a viable and desirable product will decrease, dropping their survival chances accordingly. The employment values present similar data, with 91.39% of employees being employed at low-tech firms. Furthermore, the average number of employees for high-tech firms is of 9.644, while this number is of 7.387 for low-tech firms, which indicates that high-tech ones are, on average, larger.

In order to understand how firms in both environments face different survival chances, we calculate the percentage of surviving firms and closures for both technological intensities. The results are presented in Table 5:

Table 5 - Percentage of closures by technological intensity

	High-tech	Low-tech	Count
Surviving firms	66.87%	65.08%	14473
Closures	33.13%	34.92%	7725
Count	1443	20755	22198

The percentage of surviving firms is slightly lower for low-tech firms (65.08%) than for those in high-tech ones (66.87%), which seems to go against what was discussed in the literature review, and H1. However, we must emphasise once more that this analysis is just a preliminary one.

4.5.6 - Innovation investment

Our analysis also considered the presence or absence of innovative activity undertaken by firms, distinguishing between innovators and non-innovators, following the procedure described in section 4.1.

Our sample has 2126 firms that obtain the status of innovators at least once (9.57% of the total number of firms). This means that the majority of Portuguese manufacturing firms are making little investment when it comes to innovation. In fact, the number of firms who invested at least once in innovative activities is 7535 (33.94% of the total number of firms). This reveals that 66.06% of firms in the Portuguese manufacturing industry did not invest in innovation even once during the period in which they were active in our sample. As discussed in the literature review, investment in innovation increases the probabilities of survival of both new entrants and incumbents, by easing the adaptation to possible environmental changes (Audretsch, 1995; Cefis & Marsili, 2006). As such, innovation is expected to play a significant role in firm survival for all the firms in the industry, and firms that do innovate are expected to experience higher survival chances than those that do not invest in innovation.

When it comes to size, the average number of employees for innovators is of 9.152, being on average larger than that for non-innovators, for which this value is of 7.349. As firm size has been shown to be positively related to firm survival (Bruderl et al., 1992; Mata & Portugal ,1994), this can be an indicator that firms who innovate have a stronger chance at surviving.

As done for the previous determinants of firm survival, we calculate the closure percentages, in this case for innovators vs non-innovators. However, as we have described, due to the way we define innovators, we cannot simply state that a firm is an innovator or not, as this is a status that may change, depending on the investment each firm makes throughout the years. As such, for this analysis we use only the last observation available for each firm. Considering that the last observation of each firm often coincides with the year of its death, using only this value will necessarily bias our results, since the characteristics of firms that lead them to fail may be related with the non-investment in innovative activities, which will be reflected in the data. This same issue will also be valid for the results regarding exporting activities. As such, the data presented in Tables 6, 7, 10 and 11 (the ones that present results regarding exporting activities and innovative activities) should be analysed taking into account this important remark.

Table 6 - Percentage of closures for innovators and non-innovators

	Innovators	Non-innovators	Count
Surviving firms	60.20%	65.39%	14473
Closures	39.80%	34.61%	7725
Count	814	21384	22198

Statistics computed using only the last observation of each firm

Innovators present lower survival percentages (60.20%) than those presented by non-innovators (65.39%). This suggests that investing in innovation can lower the survival probabilities of firms. However, only 814 firm had the status of innovators on their last period of activity described in the dataset. As such this description is solely informative and we do not mean to make any conclusions at this stage.

4.5.7 - Exports

For our analysis regarding exports, we distinguish between exporters and non-exporters, following the same procedure described in section 4.1.

The number of firms who have positive values of exports at least once is of 15927, which accounts for 71.75% of firms. On the other hand, only 4754 firms acquired the status of exporters at least once, which accounts for 21.42% of firms. This indicates that even though firms are exporting, the values of such exports are still below the mean of the other incumbents. The average number of employees for exporters is of 12.157, a much larger value than that presented by non-exporters, for which the value is of 6.147.

Once more, we calculate the closure percentages for the exporters and for non-exporters, with the results being displayed in Table 7:

Table 7 - Percentage of closures for exporters and non-exporters

	Exporters	Non-exporters	Count
Surviving firms	82.13%	61.65%	14473
Closures	17.87%	38.35%	7725
Count	3849	18349	22198

Statistics computed using only the last observation of each firm

As expected, exporters present higher survival chances (82.13%) than non-exporters (61.65%), which goes in accordance with what is described in the relevant literature (Bernard & Jensen, 1995; Bernard & Wagner, 1997; Wagner, 2012).

4.5.8 - Differences between categories of technological intensity

As discussed, different levels of technological intensity may affect differently firms of different sizes (Agarwal & Audretsch, 2001). As such, we analyse if the impact of the variables we have been describing so far in the survival chances of firms is different for high-tech firms and for low-tech firms. The results of the percentage of closures by technological intensity, for each variable, are displayed in the following tables:

Table 8 - Percentage of closures by current size class and technological intensity

	1 employee	2 to 5 employees	6 or more employees	Count
Surviving high-tech firms	55.37%	69.62%	81.77%	965
High-tech closures	44.63%	30.38%	18.23%	478
Surviving low-tech firms	53.40%	69.76%	71.69%	13508
Low-tech closures	46.60%	30.24%	28.31%	7247
High-tech firm count	596	474	373	1443
Low-tech firm count	6682	7722	6351	20755

As seen in Table 8, for both technological intensities, the larger the size class, the larger the surviving percentage of firms is, which indicates that size is indeed an important characteristic of firm dynamics when considering firm survival. The ones that present the highest survival percentages are high-tech firms with six or more employees, which boast 81.77%, more than 10% more than the surviving percentages of low-tech firms in the same size class. This may indicate that size is more advantageous for firms in high-tech environments than for those in low-tech ones. As discussed, larger firms have access to more resources than smaller ones, which may be a must in a high-tech environment, characterised by its higher uncertainty and more need for innovation in order to boost survival prospects (Audretsch & Mahmood, 1994). Since innovation investment is a very resource intensive activity, larger firms may clearly be at an advantage when it comes to this, which may explain this difference in survival percentages.

Table 9 - Percentage of closures by firm start-up size class and technological intensity

	1 employee	2 to 5 employees	6 or more employees	Count
Surviving high-tech firms	64.73%	70.99%	71.14%	826
High-tech closures	35.27%	29.01%	28.86%	401
Surviving low-tech firms	65.40%	71.88%	65.95%	11347
Low-tech closures	34.60%	28.12%	34.05%	5388
High-tech firm count	723	355	149	1227
Low-tech firm count	7673	5946	3116	16735

For the case of firm start-up size, Table 9 shows that, for both high-tech and low-tech firms, the ones that start with only one employee are the ones that present the lower survival percentages (64.73% for high-tech firms, 65.40% for low-tech ones). However, even though for the case of high-tech firms, larger start-up size classes are always related to higher survival percentages, for low-tech firms, the ones that start with six or more employees have lower survival percentages than those that start with between two and five employees (65.95% and 71.88%, respectively). This suggests that starting too big may actually be a disadvantage for low-tech firms, but not for high-tech ones.

Table 10 - Percentage of closures for innovators and non-innovators, by technological intensity

	Innovators	Non-innovators	Count
Surviving high-tech firms	84.21%	66.16%	965
High-tech closures	15.79%	33.84%	478
Surviving low-tech firms	58.39%	65.34%	13508
Low-tech closures	41.61%	34.66%	7247
High-tech firm count	57	1386	1443
Low-tech firm count	757	19998	20755

Statistics computed using only the last observation of each firm

As presented in Table 10, high-tech innovators present larger survival probabilities than high-tech non-innovators (84.21% and 66.16%, respectively) and the opposite happens for low-tech firms, with innovators presenting 58.39% of surviving firms, and this value for non-innovators being of 65.34%. High-tech industries are characterized by fast technological change, which may lead to obsolescence of older technologies at a fast pace (Agarwal & Gort, 2002), which leads to greater technological uncertainty, making it harder for firms in such an environment to adapt (Audretsh & Mahmood, 1994). As such, successful innovative activity is a must in a high-tech environment, since it allows firms to better tackle the inherent environmental uncertainty, by providing superior capabilities of development and survival (Audretsch, 1995; Utterback & Abernathy, 1975). Due to this, innovators showing higher survival chances than non-innovators in these conditions is to be expected. For low-tech firms, even though innovation may not play such a crucial role, it still is relevant to increase the adaptative capabilities of firms, and as such, it should be expected that innovators would present higher survival chances than non-innovators, which the data shown in Table 10 does not indicate. The analyses presented in Chapter 5 further clarifies this issue.

Table 11 - Percentage of closures for exporters and non-exporters, by technological intensity

	Exporters	Non-exporters	Count
Surviving high-tech firms	83.58%	61.82%	965
High-tech closures	16.42%	38.18%	478
Surviving low-tech firms	81.99%	61.64%	13508
Low-tech closures	18.01%	38.36%	7247
High-tech firm count	335	1108	1443
Low-tech firm count	3514	17241	20755

Statistics computed using only the last observation of each firm

Finally, Table 11 presents the surviving percentages for exporters and non-exporters, for both high-tech and low-tech firms. For both cases of technological intensity, exporters present higher surviving percentages than non-exporters, with 83.58% of surviving high-tech firms and 81.99% of surviving low-tech firms. As we may observe, the values are similar for both scenarios, and indicate that exporters are favoured to survive, no matter the technological intensity.

5 - Results

In this section we present the results of the econometric analyses we performed and discuss them in the light of the literature review. We test the hypotheses that were previously formulated, by estimating six models, each with different combinations of the variables that we have been analysing so far. For all the models we also controlled for region and variations of unemployment rate and GDP, from the years 2007 to 2014.

The models were constructed according to the characteristics of our dataset and to the scope of our analyses. Models 1 and 2 include the variables age, current size, exporter, innovator and technological intensity. The variables innovator, exporter and technological intensity are categorical and binary, taking the value of 1 for firms that are innovators, firms that are exporters, and for high-tech firms, respectively. The difference between the two models is in the definition of current size. In Model 1 we use the logarithm of current size, as it allows us to interpret the impact that a 1% increase in this variable has on the dependent variable. In Model 2 we analyse the impact of current size divided into the size classes that were previously analysed on Chapter 4. Models 3 and 4 use the same variables as Models 1 and 2, replacing current size with start-up size. The difference between the two models is that Model 3 uses the logarithm of start-up size (for the same reasons explained for the case of current size), while Model 4 analyses the impact of start-up size divided into the same classes as current size was. In Model 5 we analyse the same variables as before, but take both the logarithm of start-up size and logarithm of current size into account. Lastly, in Model 6, we analyse the same variables as in Model 5, but instead of using the logarithms, we consider both current size and start-up size divided into the same classes as before. It is important to note that current size and start-up size are highly correlated ($\rho = 0.717$ for the logarithms), which can lead to the existence of a confounding effect, which does not allow us to isolate the contribution that each of the variables has on survival. However, considering that both are important variables that affect the survival of firms, not including one of them in any of the models could lead to an omitted variable bias, which would lead to incorrect estimates. Taking all this points into consideration, since we intend to analyse the contribution of both current size and start-up size, we estimate them in models in which they are both included, as well as in models in which only one of them is included at a time.

For all categorical variables, the base levels are not presented (age = 1 year, current size and start-up size = 1 employee, non-exporters, non-innovators, low-tech firms). These base levels are the ones against which the results in the data are compared.

Table 12 shows the average marginal effects for the predicted hazard in each model, for all variables. A “predictive margin” is a statistic computed from predictions from a model while manipulating the values of the covariates, if some covariates are not fixed. The marginal effects are the differences in levels of margins if the covariate values are changed. As such, the values in Table 12, for discrete variables represent the average difference between the predicted hazard for each class and the base level of that variable, and for continuous variables represent the impact that a 1% change on the variable has on the hazard (since we are using them in logarithmic form). Therefore, negative values of the marginal effects are associated with lower hazard and longer survival times, and positive values are associated with increased hazard and shorter survival times.

In Table 12 we display the marginal effects calculated using only the last observation that each firm has in our sample.[2] By following this procedure, we avoid the bias that would result if we were to consider all observations that each firm has in the sample, since older firms would contribute more to these results.

Table 12 - Marginal effects on the hazard, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.052*** (0.002)	0.054*** (0.002)	0.035*** (0.003)	0.036*** (0.003)	0.046*** (0.003)	0.048*** (0.003)
Age: 5 to 6 years	0.060*** (0.003)	0.062*** (0.003)	0.035*** (0.004)	0.036*** (0.004)	0.047*** (0.004)	0.050*** (0.004)
Age: 7 years and older	0.048*** (0.003)	0.049*** (0.003)	0.019*** (0.006)	0.021*** (0.006)	0.031*** (0.006)	0.033*** (0.006)
Log of current size	-0.029*** (0.001)				-0.060*** (0.002)	
Firm size: 2 to 5 employees		-0.073*** (0.003)				-0.116*** (0.005)
Firm size: 6 or more employees		-0.083*** (0.003)				-0.140*** (0.005)
Log of start-up size			-0.007*** (0.001)		0.037*** (0.002)	
Start-up size: 2 to 5 employees				-0.030*** (0.002)		0.027*** (0.003)
Start-up size: 6 or more employees				-0.016*** (0.003)		0.097*** (0.007)
Innovator (binary)	-0.012** (0.004)	-0.012** (0.004)	-0.030*** (0.005)	-0.029*** (0.005)	-0.028*** (0.005)	-0.027*** (0.005)
Exporter (binary)	-0.019*** (0.003)	-0.023*** (0.003)	-0.037*** (0.004)	-0.039*** (0.004)	-0.026*** (0.004)	-0.029*** (0.004)
High-tech firm (binary)	-0.012*** (0.004)	-0.015*** (0.004)	-0.001 (0.004)	-0.001 (0.005)	-0.004 (0.005)	-0.007 (0.005)
Log-likelihood	-16809.402	-16655.818	-14066.869	-14013.128	-13578.719	-13461.624
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	22198	22198	17962	17962	17962	17962

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

It is relevant to mention that, as we can see by comparing Models 1 and 2 with Models 3, 4, 5 and 6, the number of firms analysed decreases from 22198 to 17962. This happens because for Models 3, 4, 5 and 6 we are analysing the effects of start-up size, which leads to us having to discard the firms whose

[2] For reference, the results including all observations of each firm are presented in Table B of the Appendix.

year of birth is prior to 2007, as our dataset does not provide the year of birth for those, making it impossible to assess the impact that this variable has on survival, for such firms.

By looking at the findings for Model 1, we can assess that current size has a negative impact on the hazard, suggesting a statistically significant decrease of 2.9 percentage points in the hazard associated with a 1% increase in current size, holding other variables constant. Model 2 further supports this finding – when compared to firms with only one employee, the expected decrease in hazard is of 7.3 percentage points for firms with two to five employees, and of 8.3 percentage points for firms with six or more employees. The findings suggest that larger firms face lower risk of exit than their smaller counterparts, as proposed by H5.

For the case of start-up size, Model 3 shows that the average marginal effect on hazard associated with an increase of 1% in start-up size is 0.7 percentage points, indicating that start-up size has a negative impact on hazard. Model 4 shows that firms that start with between two to five employees and firms that start with six or more employees present hazards lower than those that start with just one employee, which suggests that these findings support H6. However, while firms with start-up size of between two to five employees present a hazard about 3 percentage points lower than those with start-up size of one employee, firms with start-up size of six or more employees present a hazard only about 1.6 percentage points lower than those with start-up size of one employee. These results suggest that firms within the largest start-up size class are not associated with the lowest hazard, which indicates that firms may in fact start too big. This may be evidence that some firms start with more initial endowments than they should ideally have, which creates larger fixed costs, leading to a decrease in their chances of survival (Cooley & Quadrini, 2011). Furthermore, in order to obtain these initial endowments, firms may be getting into debt. If the success and revenue of such firms is not sufficient, they may not be able to sustain this debt, which can make it so that exiting the industry is the correct choice (Mata & Cabral, 2003). All these scenarios may imply that the managers were overly confident on how capable their firms would be in the market. However, as stated by Jovanovic (1982), the initial period of a firm's life is a trial one, in which the future success of the firm is often uncertain. The only way by which firms are capable to assess just how well adapted they are is by actually being active in an industry. As such, initial overestimation of a firm's capacity will create disadvantages that, with time, become apparent if the firm does not adapt adequately to the industry, leading to increases in the hazard rates.

Models 5 and 6 include estimations for both start-up size and current size. We can see that, when considering the control of all variables, including current size, start-up size presents positive marginal effects. As we had stated, these variables are highly correlated ($\rho = 0.717$ for the logarithms). This correlation makes it so that the best results are obtained for models in which only one of these variables at a time is considered. Similar findings had already been obtained by Mata et al. (1995), that state that current size is a better predictor of the survival prospects of a firm than initial size, as it contains information on how a firm reacts to the success it has on the industry over time.

For the binary variables representing innovators, all models present negative marginal effects, which goes in accordance with the findings in the literature, confirming H7. The relationship between survival and being an exporter is similar to the case of innovators, with the marginal effects displayed in Table 12 being lower than zero for all models, confirming H8.

When considering the effect of technological intensity, Model 1 indicates that, when compared with low-tech firms, high-tech firms boast an expected decrease in hazard of 1.2 percentage points, while Model 2 indicates a decrease of 1.5 percentage points. However, for Models 3, 4, 5 and 6, this binary variable describing technological intensity is not statistically significant. One possible explanation for this is that there exists some correlation between the variables regarding technological intensity and start-up size ($\rho = -0.171$ for the logarithm of start-up size and technological intensity). Due to this correlation, the better results are obtained when only one variable at a time is consider in the models. When both are present in the same model, the effect of the technological intensity itself is not enough to allow us to draw conclusions regarding its effect on firm survival. In order to further support this explanation, we estimate Models 1 and 2, but utilizing the sample that we utilize for Models 3 to 6.[3] The results we obtain are statistically significant when it comes to the impact of technological intensity on survival, which supports that the correlation with start-up size might lead to non-significant results.

The results mentioned in the previous paragraph are vastly similar to the ones obtained by Mata and Portugal (1999), that also studied the Portuguese manufacturing industry, but following the firms created in 1983. In their study, they also find that the hazard decreases as the industry's technological intensity increases, but do not obtain significant results for some of the models they test. However, although the coefficients their models present may not be statistically significant, the estimated coefficients are always negative and the coefficients regarding high-tech firms are always more negative than the ones regarding medium and low-tech firms. As we can see, such findings are in line with the ones we obtain, once more indicating that the factors that characterized the Portuguese manufacturing industry in the eighties remain mostly true.

Concluding the analysis on the impact of technological intensity, there is a strong indication that, in our sample, high-tech tech firms are indeed the ones with the higher survival chances, just as the Kaplan-Meyer survival estimates had initially indicated. As such, our findings do not support H1, suggesting instead that high-tech firms present lower hazards than low-tech ones.

Lastly, when looking at all of the age classes, for all models, the results show that the marginal effects are positive, which means that the lowest hazard is for the base level, which includes the firms with age equal to 1 year. The hazard increases from the class of age 2-4 years to age 5-6 years, but then, for all models, starts decreasing when it reaches the 7-year mark (though still larger than in the first period).

[3] For reference, the results for Models 1 and 2 using the smaller sample that was used to obtain Models 3 to 6 are presented in Table C of the Appendix.

These results seem to be in line with the theory of the "liability of adolescence" that states that, during the first periods of activity, firms still have resources that were gathered at the time of birth and that are being used up. These resources may help them survive the first period of their lives, even if their results are not ideal. However, after the initial resources are used up, if the firms do not find success in their market, exiting may be the correct call. This course of action leads to higher closure rates on the years immediately after the first few of activity (Brüderl & Schüssler, 1990; Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991).

We compared each age class with the preceding age class (rather than against the base class, as we have been doing up until now), so as to obtain confirmation on this hypothesis.[4] For Models 1 and 2, the results show that all of these differences are statistically significant, which helps guarantee that the "liability of adolescence" better describes our samples. However, for Models 3 to 6 the difference between the age class of five to six years and the age class of two to four years is not significant, which indicates that, for these models, the hazard most likely reaches a maximum earlier than for Models 1 and 2. The different results once more are related to the different sample used between Models 1 and 2 and Models 3 to 6.

Due to its characteristics, the theory of the "liability of adolescence" leads to an inverted U-shaped hazard functions – during the first period of a firm's activity, death risks are low, but then grow, only to decrease monotonically later on in the firm's life (Esteve-Pérez & Mañez-Castillejo, 2008). To better visualise the evolution of the hazard with firm age for the case of our sample, we analyse the baseline hazard function, for Models 1 and 6. The results regarding Model 1 are displayed in Figure 13, and the results regarding Model 6 are displayed in Figure 14. By displaying the results for both these models, we are able to ascertain if there are differences in the baseline hazard functions when we consider the entirety of our sample that we use in Model 1 compared to when we consider the smaller sample used for Model 6. We do not display the results for the other models, as we are interested in analysing the shape of the baseline hazard functions, and the shape of the function obtained when analysing Model 2 is the same as the one obtained when analysing Model 1 and the shape of the functions obtained when analysing Models 3, 4 and 5 are the same as the one obtained when analysing Model 6.

[4] For reference, the results displaying the contrasts for Models 1 to 6 are presented in Table D of the Appendix.

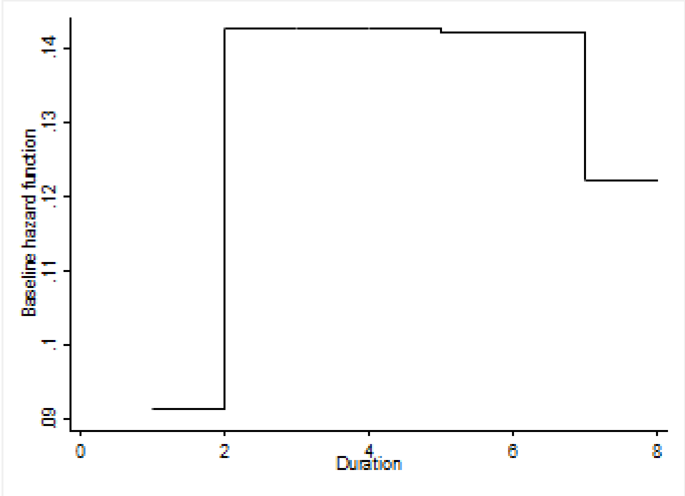

Figure 13 - Baseline hazard function, for all firms, for Model 1

Figure 14 - Baseline hazard function, for all firms, for Model 6

Analysing Figure 13, we see that the hazard grows until the seventh year of activity of firms, decreasing monotonically from then on. On the other hand, looking at Figure 14, we see that the hazard maximum is reached earlier, as we had already suggested. Nonetheless, despite the differences, both figures are in line with the inverted-U shape hazard function that describes the “liability of adolescence”, further supporting that this is the theory that better describes our data.

The literature commonly affirms that, when this inverted-U shape hazard rate is found, the hazard maximum takes place around the second to third year of activity of firms (for example, Esteve-Pérez & Mañez-Castillejo, 2008; Fichman & Levinthal, 1991). However, some authors present results for which this maximum is found on later years of activity: Brüderl and Schüssler (1990) point out that for businesses in the commercial register in the Munich area, from 1980 to 1989, the hazard maximum takes place between the fifth to sixth year of firms’ activity and Mahmood (2000) states that for high-tech firms present in the U.S. Business Administration’s Small Business Database, the hazard maximum takes 3.5 to 4 years to be reached. Studies have also shown that even when inverted-U shaped hazard rates are present, different firm characteristics will change the time at which the hazard maximum occurs. Brüderl and Schüssler (1990) affirm that, the higher the initial endowments, the longer the duration of adolescence, and therefore the peak in the population's hazard function should be later in these cases.

To understand if differences exist between technological intensities in our dataset, we now present the baseline hazard functions for both high-tech and low-tech firms separately. We will analyse the results for Models 1 and 6, for both levels of technological intensity. The results for high-tech firms are displayed in Figure 15 (Model 1) and Figure 17 (Model 6) and for low-tech firms are displayed in Figure 16 (Model 1) and Figure 18 (Model 6).

Figure 15 - Baseline hazard function, for high-tech firms, for Model 1

Figure 16 - Baseline hazard function, for low-tech firms, for Model 1

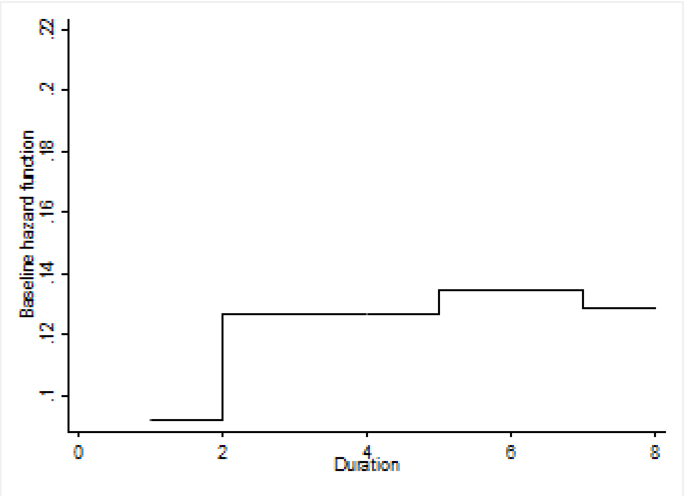

Figure 17 - Baseline hazard function, for high-tech firms, for Model 6

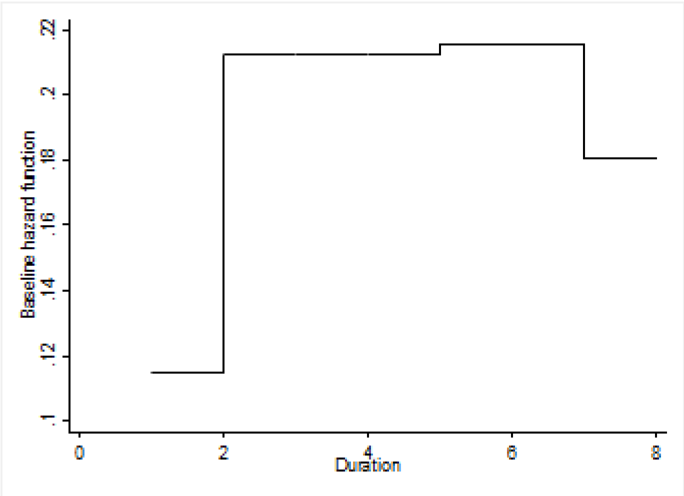

Figure 18 - Baseline hazard function, for low-tech firms, for Model 6

Comparing Figure 15 with Figure 16 and Figure 17 with Figure 18, we observe that the hazard starts decreasing when the seven-year mark is reached, for both levels of technological intensity and for both models. However, the decrease is more pronounced in the case of low-tech firms, which indicates that the impact of learning is more visible in a low-tech environment than in a high-tech one. As such, the capabilities that firms acquire by learning from experience, with prolonged activity in their industries, are more impactful in low-tech environments than in high-tech ones. As mentioned by Ericson and

Pakes (1995), firms invest to enhance profit-earning capabilities in an environment characterized by substantial competitive pressure from both within and outside the industry. What our results seem to suggest is that this profit-earning capabilities may play a greater role in low-tech environments.

Concluding the analysis regarding the impact of age on firm survival, H1 is supported, but the most common case of the "liability of newness" is not the one that better describes our data, but rather the "liability of adolescence".

A focal goal of this dissertation is to understand the difference that technological intensity has on the impact that the studied variables may have on firm survival. To do so, in Tables 13 and 14 we present the results of econometric analyses that are similar to the ones that lead to the results presented on Table 12. However, the difference between the models shown in Tables 13 and 14, and the ones shown in Table 12 is that we do not consider the variable regarding technological intensity. Instead, Table 13 presents the results regarding only high-tech firms, and Table 14 only low-tech firms. Once more, we calculate the marginal effects using only the last observation of each firm, for the same reasons mentioned up until now.[5]

Table 13 - Marginal effects on the hazard, for high-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.030*** (0.008)	0.031*** (0.008)	0.018** (0.010)	0.019** (0.010)	0.028*** (0.010)	0.028*** (0.010)
Age: 5 to 6 years	0.046*** (0.009)	0.046*** (0.009)	0.019* (0.015)	0.021* (0.015)	0.035** (0.016)	0.035** (0.016)
Age: 7 years and older	0.044*** (0.011)	0.042*** (0.011)	0.013 (0.022)	0.015 (0.023)	0.030 (0.025)	0.029 (0.025)
Log of current size	-0.033*** (0.005)				-0.063*** (0.009)	
Firm size: 2 to 5 employees		-0.052*** (0.008)				-0.095*** (0.016)
Firm size: 6 or more employees		-0.074*** (0.009)				-0.124*** (0.017)
Log of start-up size			-0.012* (.007)		0.033*** (0.008)	
Start-up size: 2 to 5 employees				-0.029*** (0.009)		0.029* (0.015)
Start-up size: 6 or more employees				-0.022* (0.014)		0.106*** (0.035)
Innovator(binary)	-0.049** (0.023)	-0.052** (0.024)	-0.098*** (0.034)	0.099*** (0.034)	-0.085** (0.035)	-0.088** (0.035)
Exporter(binary)	-0.009 (0.010)	-0.014 (0.010)	-0.039*** (0.015)	-0.039*** (0.015)	-0.022* (0.013)	-0.026* (0.015)
Log-likelihood	-1076.565	-1065.842	-948.079	-981.374	-951.688	-948.309
Number of firms	1443	1443	1227	1227	1227	1227
Number of observations	1443	1443	1227	1227	1227	1227

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

[5] For reference, the results including all the observations of each firm are presented in the Appendix, in Table E for high-tech firms, and in Table F for low-tech firms.

Table 14 - Marginal effects on the hazard, for low-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.053*** (0.002)	0.056*** (0.002)	0.036*** (0.003)	0.037*** (0.003)	0.047*** (0.003)	0.049*** (0.003)
Age: 5 to 6 years	0.061*** (0.003)	0.063*** (0.003)	0.036*** (0.004)	0.037*** (0.004)	0.048*** (0.004)	0.051*** (0.004)
Age: 7 years and older	0.049*** (0.003)	0.051*** (0.003)	0.020*** (0.006)	0.022*** (0.006)	0.031*** (0.006)	0.033*** (0.006)
Log of current size	-0.029*** (0.001)				-0.059*** (0.002)	
Firm size: 2 to 5 employees		-0.075*** (0.003)				-0.119*** (0.005)
Firm size: 6 or more employees		-0.084*** (0.003)				-0.142*** (0.006)
Log of start-up size			-0.007*** (0.001)		0.037*** (0.002)	
Start-up size: 2 to 5 employees				-0.031*** (0.003)		0.026*** (0.003)
Start-up size: 6 or more employees				-0.016*** (0.003)		0.096*** (0.008)
Innovator(binary)	-0.009** (0.005)	-0.009** (0.005)	-0.028*** (0.005)	-0.026*** (0.005)	-0.026*** (0.005)	-0.024*** (0.005)
Exporter(binary)	-0.019*** (0.003)	-0.024*** (0.003)	-0.037*** (0.004)	-0.039*** (0.004)	-0.026*** (0.004)	-0.030*** (0.004)
Log-likelihood	-16809.402	-16655.818	-14066.869	-14013.128	-13578.719	-13461.624
Number of firms	20755	20755	16735	16735	16735	16735
Number of observations	20755	20755	16735	16735	16735	16735

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

As we can observe, the variables in Tables 13 and 14 follow the same overall tendencies as they did in the results shown in Table 12. However, we must emphasise that the results displayed in Tables 13 and 14 are not directly comparable, since they use two different samples, one for each level of technological intensity. As such, we need to analyse both tables individually.

Once more, regarding age, for both technological intensities, the marginal effects only start decreasing for the larger age class, which suggests that the “liability of adolescence” is the best fit for both cases. However, by comparing the marginal effects presented in both tables, we can see that the difference between the values for the age class of seven or more years and the age class of five to six years is larger for the case of low-tech firms than for the case of high-tech ones. As we had discussed when comparing Figures 15 to 18, the decrease in hazard is more pronounced for low-tech firms than for high-tech ones, explaining the difference between both technological intensities when it comes to the marginal effects between the two age classes aforementioned.

When considering both current firm size and start-up size, we can see that, no matter the technological intensity, both remain negatively correlated with hazard. However, for the case of start-up size, the largest class of six or more employees once more presents less negative marginal effects then the class of start-up size between two and five employees, which suggest that starting too big can in fact be a disadvantage, for both high-tech and low-tech industries.

Additionally, Models 5 and 6 indicate once more, that when both current size and start-up size are considered in the same model, together with all other variables and controls, the hazard ratio for start-up size is larger than one. As such, we can ascertain that the high correlation between these variables remains true for both technological intensities (for the logarithms, $\rho = 0.655$ for high-tech firms, and $\rho = 0.719$ for low-tech firms). Due to this, it remains true that only considering one of these variables at a time in each model leads to better results.

Lastly, regarding innovators and exporters, all models, for both high-tech and low-tech firms show values of marginal effects lower than zero, indicating that investment in innovation and exports are positively correlated with firm survival for both levels of technological intensity.

Finally, we present the results for models that take into account interaction terms between the variables and the level of technological intensity. An interaction effect is one in which the partial effect on the dependent variable with respect to an explanatory variable may depend on the effect of another explanatory variable. As such, this analysis allows us to understand the effect that the variables can have upon other variables. By estimating interaction terms with technological intensity, we aim to understand how the impact of the variables on survival is different for high-tech and low-tech firms. Furthermore, following this procedure we are now able to compare the marginal effects for the results obtained regarding high-tech and low-tech firms, which we have not been able to do up until this point.

For the results regarding the variables age, innovator and exporter, the models used are an expansion of Model 1. For the results regarding the current firm size divided into classes, the model used is an expansion of Model 2. For the results regarding the start-up size divided into classes, the model used is an expansion of Model 4. The results are shown in Table 15 and Figures 19 to 23. Once more, we only utilize the last observations of each firm, for the same reasons mentioned up until now.[6]

[6] For reference, the results in the form of a table regarding all the observations of each firm are presented in Table G.

Table 15 - Marginal effects on the hazard, for the models with interaction terms, for all firms

	High-tech	Low-tech
Age: 2 to 4 years	0.032*** (0.008)	0.053*** (0.002)
Age: 5 to 6 years	0.043*** (0.009)	0.061*** (0.003)
Age: 7 years and older	0.038*** (0.010)	0.049*** (0.003)
Firm size: 2 to 5 employees	-0.058*** (0.009)	-0.074*** (0.003)
Firm size: 6 or more employees	-0.082*** (0.009)	-0.083*** (0.003)
Start-up size: 2 to 5 employees******	-0.029*** (0.009)	-0.030*** (0.003)
Start-up size: 6 or more employees******	-0.023 (0.013)	-0.016*** (0.003)
Innovator(binary)	-0.038*** (0.012)	-0.009** (0.004)
Exporter(binary)	-0.014 (0.009)	-0.018*** (0.003)
Log-likelihood	-15533.22	-15132.37
Number of firms	1443	20755
Number of observations	1443	20755

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
**** For statistics considering start-up size, the number of observations and the number of firms is of 1227, for high-tech firms and of 16735 for low-tech firms.

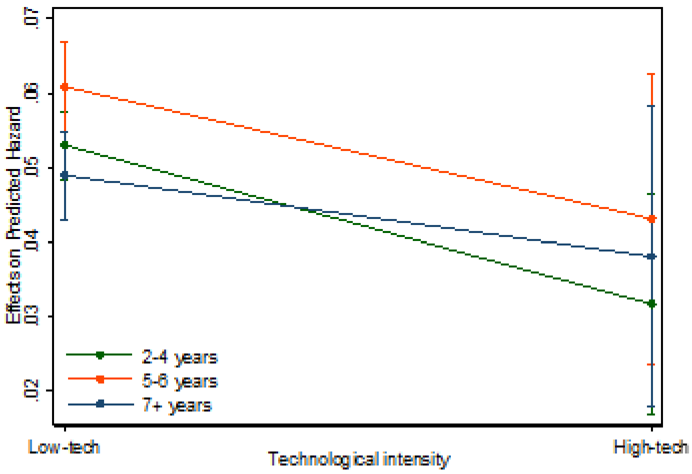

Figure 19 - Marginal effects for the interaction between each age class and both levels of technological intensity

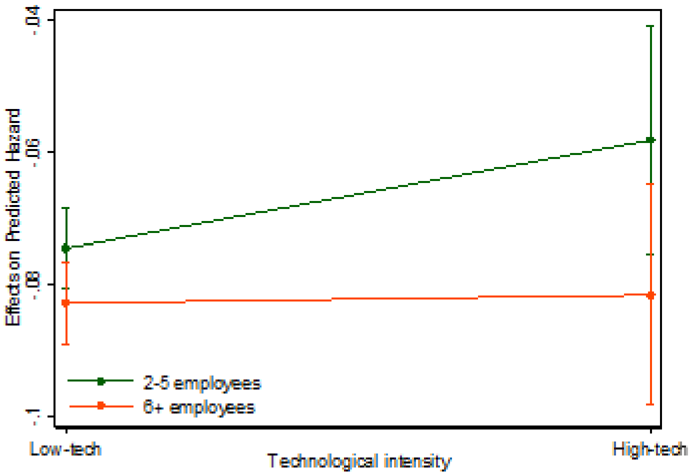

Figure 20 - Marginal effects for the interaction between each current firm size class and both levels of technological intensity

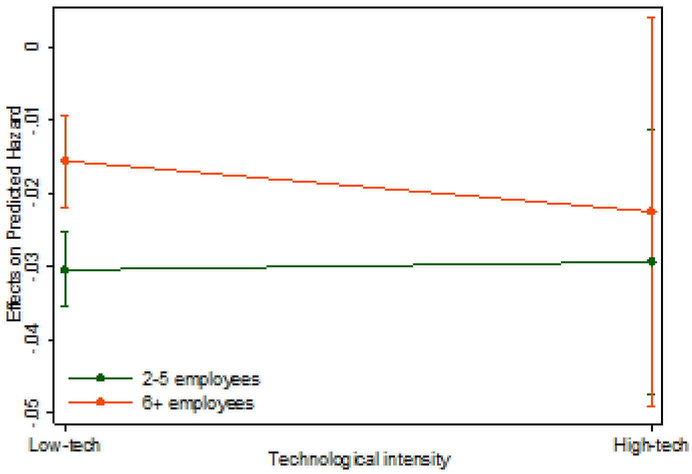

Figure 21 - Marginal effects for the interaction between each start-up size class and both levels of technological intensity

Figure 22 - Marginal effects for the interaction between innovators and both levels of technological intensity

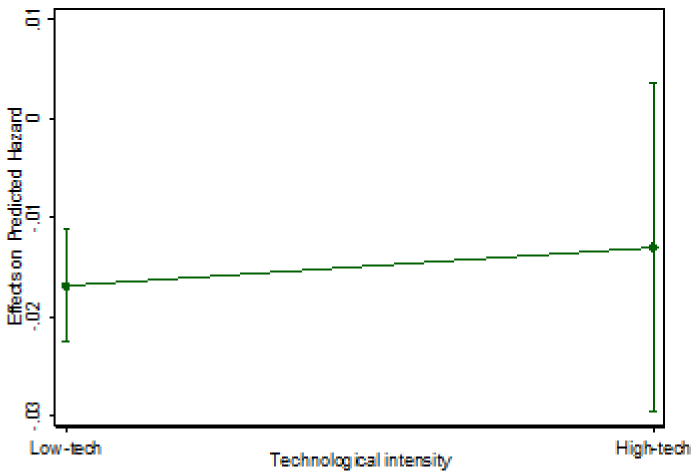

Figure 23 - Marginal effects for the interaction between exporters and both levels of technological intensity

The results shown in Table 15 and in Figures 19 to 23 are the predicted marginal effects on the hazard for both levels of technological intensity, for all the categorical variables. Each of the results in each figure and result in Table 15 indicates the difference in marginal effects between that particular class and the base level of that variable, for either high-tech or low-tech firms. As such, using concrete examples, the difference in the hazard between low-tech innovators and low-tech non-innovators is of 0.9 percentage points (as seen in Table 15 and Figure 22), and the difference in the hazard between high-tech firms with firm size between two to five employees and high-tech firms with firm size of one employee is of 5.8 percentage points (as seen in Table 15 and Figure 20).

First, by looking at Figure 23, we can ascertain that high-tech exporters obtain results that are not significant, since the confidence interval for this result englobes both positive and negative values. This result indicates that we cannot affirm that high-tech exporters face lower hazard than high-tech non-exporters. In fact, the results displayed in Table 13 already indicated this, and this result further confirms that finding. Furthermore, looking at Figure 21, we can also see that the result regarding high-tech firms with start-up size of six or more employees does not present significant results. This once more seems to indicate that firms can in fact start too big.

Secondly, only for the case of the interaction between the variables innovator and technological intensity (displayed in Figure 22) are the results significantly different between high-tech and low-tech firms (because the bands representing the 95% confidence interval do not overlap their values for this variable). The results for both technological intensities are negative, which means that both high-tech and low-tech innovators face lower hazard than their non-innovator counterparts. Furthermore, since high-tech firms obtain a larger decrease in predicted hazard than low-tech ones, we can affirm that high-tech firms benefit more from being innovators than their low-tech counterparts, confirming H3.

On the other hand, by looking at Figures 20 and 21, the results do not allow us to confirm if the hazard is significatively different for any size class, neither regarding current firm size nor regarding start-up size. As such, we are unable to confirm H2, since we cannot tell with certainty if there exists a difference in hazard for high-tech and low-tech firms, for any of the size classes.

As we mentioned in section 4.3, in order to test the robustness of our models, we also present the results we obtain by running them using both the Weibull model and the Cox model.[7] Given the different shapes of the piecewise constant, Weibull and Cox functions, the results will necessarily be somewhat different. However, if our models are robust, the results should be similar. We present the results in the form of hazard ratios, and not marginal effects, since the predicted hazard necessary to calculate the marginal effects cannot be calculated by the software we are using in the exact same way for the three models. However, even though the information conveyed may be displayed in a different form, the conclusions to be drawn are the same as the ones we have been drawing up until now when looking at marginal effects. As we can see, the results obtained are all similar, which indicates we have robust models.

Summarizing our findings, regarding the main focus of this dissertation – the impact of technological intensity on survival – our results show that high-tech firms face lower hazard than low-tech firms. Such findings do not support H1, going against it. Furthermore, we do not confirm H2, since we are not able to ascertain if small firms face lower hazard in high-tech industries than in low-tech ones. Additionally,

[7] For reference, the results including all the observations of each firm are presented in the Appendix, with the results for the Piecewise function being in Tables H, I and J, for the Cox function in Tables K, L and M, and for the Weibull function in Tables N, O and P.

we find that high-tech firms do benefit more from being innovators than low-tech firms, which supports H3.

Regarding age, our findings suggest that the theory that better suits our data is the “liability of adolescence”. We find U-shaped hazard functions, with hazards increasing initially, but then decreasing monotonically. Due to this, our findings do support H4, with age and hazard being negatively correlated, but the most common theory of the “liability of newness” does not describe our sample.

Considering the rest of the firm dynamics that we analysed, our results confirm that both larger firms and firms that start with larger start-up sizes are associated with lower hazard than their smaller counterparts, supporting H5 and H6. Lastly, our results also show that innovators and exporters face lower hazard than non-innovators and non-exporters, respectively. Such findings confirm H7 and H8.

6 - Conclusions

There exists a large number of studies in the literature focused on firm dynamics and their impact on firm survival and growth. Most of these studies, which usually were of empirical basis, affirm that firm and industry dynamics are important factors that shape firm survival. Since both firm survival and growth are viewed as two of the main characteristics of any industry, their study is important to understand why some firms are more well adapted than others, and whey they will prosper further than other firms in their industry. In fact, a large body of literature tries to ascertain how the important variables of firm dynamics behave in different industries, with different characteristics, in order to understand their impact on a firm's life.

For this dissertation, our sample was constructed using data from the Integrated Business Accounts System (*Sistema de Contas Integradas de Empresas* – SCIE) provided by the Portuguese Institute of Statistics. We first provide a descriptive analysis, focusing on the number of firms and employment, in order to better understand how the characteristics of our sample influence the results. We observe that the majority of firms start small, and that a large percentage dies while still young. However, firms that survive will grow, as the average incumbent has a larger size than the average size at start-up. Nonetheless, the average firm is still of small size. We also observe that most firms are inserted in low-tech environments. Furthermore, we show that most firms do not invest in innovation, and that only a small part of firms export.

Lastly, we performed econometric analyses, considering a proportional hazards model for which we used a flexible piecewise constant specification of the baseline hazard function. For this analyses, the variables we studied were technological intensity, firm age, current firm size, firm start-up size, investment in innovation and investment in exports. By performing these analyses, we aimed to understand how these variables impact firm survival when controlling for other factors. The results we present confirm most of the hypotheses in our dissertation, going in accordance with what was expected when considering the literature review. We show that firm size, firm start-up size, investment in innovation and investment in exports have a positive impact on firm survival, lowering the hazards of exit, in line with the main results presented in the literature.

However, when considering the variables related with age and technological environment, our results differ from what we expected. When age is considered, the most common scenario is that of monotonically decreasing hazard with age, following what is usually called the "liability of newness". However, our results suggest that the hazard increases during the initial period of activity of firms, and only starts decreasing later on in their lives. This scenario is not uncommon, being usually called the "liability of adolescence". What makes our results different from the common scenario is that it takes nearly seven years for the hazard to start decreasing, while the results presented in the literature usually show a shorter time window before the hazard decreases. Although it is not unheard of for such a long period to exist, it is still uncommon, and is a characteristic of the Portuguese manufacturing industry that should be further studied.

When technological environment is considered, we suggest that firms in high-tech environments present lower hazard than the ones in low-tech environments, which does not go in accordance with the hypothesis we formulated initially. Still regarding the impact of technological intensity, we suggest that firms benefit more from being innovators in high-tech industries than in low-tech ones. Such a result goes in line with the findings in the literature, that affirm that high-tech environments are associated with greater uncertainty and technological obsolescence, which makes innovation even more relevant in high-tech industries than in low tech-ones. Lastly, we tried to ascertain if there exists a relation between technological intensity and firm size, to understand if small firms face lower hazard rates in high-tech industries than in low-tech ones. However, the results we obtain do not allow us to conclude anything in this regard.

We should also state some limitations that our models have, that may have had some impacts on the results obtained. First of all, our dataset did not contain information regarding start-up size for firms created before 2007, which meant that we could not consider those firms when studying the impact that start-up size has on firm survival, leading to a smaller sample size on four of our models. When regarding our variable that distinguishes innovators from non-innovators, we could not use any direct measurement of innovative investment, as our dataset does not provide any variable that directly relates to it. As such, by considering the sum of the variables “investment in intangible assets”, “investment in R&D” and “investment in software”, we find a way of accounting for innovative investment, but other investments that could be considered are left out, as our dataset does not provide further information. Furthermore, the data present in our dataset does not allow us to distinguish between successful and unsuccessful innovative activities, but only to ascertain the investment that was made in innovation. Successful innovation is what allows firms to gain the benefits of the investment and to boost their survival chances. By not making this distinction, we are in fact gathering both successful and unsuccessful innovators in the variable we study, which may lead to results that stray from the reality. This issue should be clarified in further studies.

Overall, our findings seem to indicate that investment in international trade and exports and investment in innovation will increase the survival chances of firms. As such, incentives for such investments could lead to an increase in firm survival and growth and should be taken into consideration in order to lead to a possible increase in economic growth. We hope the findings in this dissertation are useful for future studies on firm survival and growth.

References

Acs, Z. J., Audretsch, D. B. (1987). Innovation, market structure, and firm size. *Review of Economics and Statistics*, 69(4), 567–574.

Acs, Z. J., Audretsch, D. B. (1988). Innovation in large and small firms: An empirical analysis. *American Economic Review*, 78(4), 678–690.

Agarwal, R. (1998). Evolutionary trends of industry variables. *International Journal of Industrial Organization*, 16(4), 511–525.

Agarwal, R., Audretsch, D. B. (2001). Does entry size matter? The impact of the life cycle and technology on firm survival. *The Journal of Industrial Economics*, 49(1), 21–43.

Agarwal, R., Gort, M. (2002). Firm and product life cycles and firm survival. *American Economic Review*, 92(2), 184–190.

Allison, P. D. (1984). *Event History Analysis*. Beverly Hills: Sage Publications.

Audretsch, D. B. (1991). New-firm survival and the technological regime. *The Review of Economics and Statistics*, 73(3), 441–450.

Audretsch, D. B. (1995). Innovation, growth and survival. *International Journal of Industrial Organization*, 13(4), 441–457.

Audretsch, D. B., Keilbach M. C., Lehman, E. E. (2006). *Entrepreneurship and Economic Growth*. Oxford: Oxford University Press.

Audretsch, D. B., Mahmood, T. (1994). The rate of hazard confronting new firms and plants in U.S. manufacturing. *Review of Industrial Organization*, 9(1), 41–56.

Audretsch, D. B., Mahmood, T. (1995). New firm survival: New results using a hazard function. *Review of Economics and Statistics*, 77(1), 97–103.

Banbury, C. M., Mitchell, W. (1995). The effect of introducing important incremental innovations on market share and business survival. *Strategic Management Journal*, 16(5), 161–182.

Baldwin, J., & Yan, B. (2011). The death of Canadian manufacturing plants: Heterogeneous changes in tariffs and real exchange rates. *Review of World Economics/Weltwirtschaftliches*, 147(1), 131–167.

Bernard, A. B., Jensen, J. B. (1995). Exporters, jobs, and wages in U.S. manufacturing: 1976–1987. *Brookings Papers on Economic Activity: Microeconomics*, 67–119.

Bernard, A. B., Jensen, J. B. (2004). Why some firms export. *Review of Economics and Statistics*, 86(2), 561–569.

Bernard, A. B., Wagner, J. (1997). Exports and success in German manufacturing. *Weltwirtschaftliches Archiv*, 133(1), 134–157.

Brüderl, J., Preisendorfer, P., Ziegler, R. (1992). Survival chances of newly founded business organizations. *American Sociological Review*, 57(2), 227–242.

Brüderl, J., Schüssler, R. (1990). Organizational mortality: The liabilities of newness and adolescence. *Administrative Science Quarterly*, 35(3), 530–547.

Buddelmeyer, H., Jensen, P. H., Webster, E. (2010). Innovation and the determinants of company survival. *Oxford Economic Papers*, 62(2), 261–285.

Caves, R. E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature,* 36(4), 1947–1982.

Caves, R. E., Porter, M. E. (1977). From entry barriers to mobility barriers: Conjectural decisions and contrived deterrence to new competition. *The Quarterly Journal of Economics*, 91(2), 241–262.

Cefis, E., Marsili, O. (2005). A matter of life and death: Innovation and firm survival. *Industrial and Corporate Change*, 14(6), 1167–1192.

Cefis, E., Marsili, O. (2006). Survivor: The role of innovation in firms' survival. *Research Policy*, 35(5), 626–641.

Christensen, C. M. (1997). *The Innovator's Dilemma: When New Technologies Cause Great Firms to Fail.* Boston, MA: Harvard Business School Press.

Cohen, W. M., Keppler, S. (1992). The anatomy of R&D intensity distributions. *American Economic* Review, 82(4), 773–799.

Cooley, T. F., Quadrini, V. (2001). Financial markets and firm dynamics. American Economic Review, 91(5), 1286–1310.

Correia, A. L., Gouveia, A. F. (2016). What determines firm-level export capacity? Evidence from Portuguese firms. *GEE papers*, 57.

Cox, D. R. (1972). Regression models and life tables. *Journal of the Royal Statistical Society*, 34(2), 187–202.

Dunne, T., Hughes, A. (1994). Age, size, growth and survival: UK companies in the 1980s. *The Journal of Industrial Economics*, 42(2), 115–140.

Edwards, K. L., Gordon, T. J. (1984). *Characterization of Innovations Introduced in the U.S. Market in 1982*. Glastonbury, CT: Futures Group and NTIS.

Ericson, R., Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *The Review of Economic Studies*, 62(1), 53–82.

Esteve-Pérez, S., Mañez-Castillejo, J. A. (2008). The resource-based theory of the firm and firm survival. *Small Business Economics*, 30(3), 231–249.

Evans, D. S. (1987a). Tests of alternative theories of firm growth. *Journal of Political Economy*, 95(4), 657–674.

Evans, D. S. (1987b). The relationship between firm growth, size, and age: Estimates for 100 manufacturing industries. *The Journal of Industrial Economics*, 35(4), 567–581.

Fichman, M., Levinthal, D. A. (1991). Honeymoons and the liability of adolescence: A new perspective on duration dependence in social organizational relationships. *Academy of Management Review*, 16(2), 442–468.

Geroski, P. A. (1995). What do we know about entry? *International Journal of Industrial Organization*, 13(4), 421–440.

Gort, M., Klepper, M. (1982). Time paths in the diffusion of product innovations. *The Economic Journal*, 92(367), 630–653.

Hall, B. H. (1987). The relationship between firm size and firm growth in the U.S. manufacturing sector. *Journal of Industrial Economics*, 35(4), 583–605.

Hall, B. H., Griliches, Z., Hausman, J. A. (1986). Patents and R&D: Is there a lag? *International Economic Review*, 27(2), 265–284.

Hannan, M. T. (1998). Rethinking age dependence in organizational mortality: Logical formalizations. *American Journal of Sociology,* 104(1), 126–164.

Heckman, J., Singer, B., (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica,* 52(2), 271–320.

Jenkins, S.P. (2005). *Survival Analysis*. Unpublished manuscript, Colchester, UK: Institute for Social and Economic Research University of Essex).

Jovanovic, B. (1982). Selection and the evolution of industry. *Econometrica*, 50(3), 649–670.

Loecker, J. (2007). Do exports generate higher productivity? Evidence from Slovenia. *Journal of International Economics*, 73(1), 69–98.

Mahmood, T. (2000). Survival of newly founded businesses: A log-logistic model approach*. Small Business Economics*, 14(3), 223–237.

Mata, J., Cabral, L. M. B. (2003). On the evolution of the firm size distribution: Facts and theory. *American Economic Review*, 93(4), 1075–1090.

Mata, J., Portugal, P. (1994). Life duration of new firms. *The Journal of Industrial Economics*, 42(3), 227–245.

Mata, J., Portugal, P. (1999). Technology intensity, demand conditions, and the longevity of firms. In: Audretsch, D. B., Thurik, A. R. (Eds.), *Innovation, Industry Evolution, and Employment* (pp. 265–279). Cambridge: Cambridge University Press.

Mata, J., Portugal, P. (2002). The survival of new domestic and foreign-owned firms. *Strategic Management Journal*, 23(4), 323–343.

Mata, J., Portugal, P., Guimarães, P. (1995). The survival of new plants: Start-up conditions and post-entry evolution. *International Journal of Industrial Organization*, 13(1), 459–481.

Nelson, R. R., Winter, S. G. (1982). *An Evolutionary Theory of Economic Change*. Cambridge: Belknap.

Pakes, A., Ericson, R. (1998). Empirical implications of alternative models of firm dynamics. *Journal of Economic Theory*, 79(1), 1–45.

Porter, M. E. (1979). The structure within industries and companies' performance. *The Review of Economics and Statistics*, 61(2), 214–227.

Rothwell, R. (1989). Small firms, innovation and industrial change. *Small Business Economics*, 1(1), 51–64.

Sarkar, M. B., Echambadi, R., Agarwal, R., Sen, B. (2006). The effects of the innovative environment on exit of entrepreneurial firms, *Strategic Management Journal*, 27(6), 519–539.

Tiziana, L., Alessandro, V. (2011). Competitiveness and productivity: A case study of Italian firms, *Applied Economics*, 43(20), 2615–2625.

Utterback, J. M., Abernathy, W. J. (1975). A dynamic model of process and product innovation. *Omega*, 3(6), 539–556.

Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, 48(1), 123–154.

Wagner, J. (1995). Exports, firm size and firm dynamics. *Small Business Economics,* 7(1), 29–39.

Wagner, J. (2012). International trade and firm performance: A survey of empirical studies since 2006. *Review of World Economics/Weltwirtschaftliches Archiv*, 148(2), 235–267.

Appendix

Table A - Manufacturing industries by technological intensity

Manufacturing industries	NACE Rev. 2 codes – 2-digit level
High-technology	**21** Manufacture of basic pharmaceutical products and pharmaceutical preparations **26** Manufacture of computer, electronic and optical products
Medium-high-technology	**20** Manufacture of chemicals and chemical products **27 to 30** Manufacture of electrical equipment, Manufacture of machinery and equipment Manufacture of motor vehicles, trailers and semi-trailers, Manufacture of other transport equipment
Medium-low-technology	**19** Manufacture of coke and refined petroleum products **22 to 25** Manufacture of rubber and plastic products, Manufacture of other non-metallic mineral products, Manufacture of basic metals, Manufacture of fabricated metal products, except machinery and equipment **33** Repair and installation of machinery and equipment
Low-technology	**10 to 18** Manufacture of food products, beverages, tobacco products, textiles, wearing apparel, leather and related products, wood and of products of wood, paper and paper products, printing and reproduction of recorded media. **31 to 32** Manufacture of furniture, Other manufacturing

Source: Eurostat (see also: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf)

Table B - Marginal effects on the hazard, for all observations of each firm, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.051*** (0.002)	0.053*** (0.002)	0.037*** (0.003)	0.037*** (0.003)	0.047*** (0.003)	0.048*** (0.003)
Age: 5 to 6 years	0.059*** (0.003)	0.060*** (0.003)	0.035*** (0.004)	0.037*** (0.004)	0.048*** (0.004)	0.050*** (0.004)
Age: 7 years and older	0.048*** (0.003)	0.048*** (0.003)	0.020*** (0.006)	0.022*** (0.006)	0.031*** (0.006)	0.033*** (0.006)
Log of current size	-0.028*** (0.001)				-0.058*** (0.002)	
Firm size: 2 to 5 employees		-0.074*** (0.003)				-0.121*** (0.005)
Firm size: 6 or more employees		-0.084*** (0.003)				-0.146*** (0.005)
Log of start-up size			-0.007*** (0.001)		0.036*** (0.002)	
Start-up size: 2 to 5 employees				-0.031*** (0.003)		0.025*** (0.003)
Start-up size: 6 or more employees				-0.016*** (0.003)		0.092*** (0.007)
Innovator(binary)	-0.011** (0.005)	-0.011** (0.004)	-0.031*** (0.005)	-0.029*** (0.005)	-0.027*** (0.005)	-0.025*** (0.005)
Exporter (binary)	-0.018*** (0.003)	-0.022*** (0.003)	-0.038*** (0.004)	-0.039*** (0.004)	-0.025*** (0.004)	-0.028*** (0.004)
High-tech firm (binary)	-0.012*** (0.004)	-0.014*** (0.004)	-0.001 (0.005)	-0.001 (0.005)	-0.003 (0.005)	-0.006 (0.005)
Log-likelihood	-16789.322	-16599.823	-14023.779	-14009.111	-13401.722	-13455.109
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	93317	93317	63483	63483	63483	63483

Statistics computed using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; start-up size = 1 employee; current size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table C - Marginal effects on the hazard, for all firms, with the sample used on Models 3 to 6

	Model 1	Model 2
Age: 2 to 4 years	0.044*** (0.003)	0.048*** (0.003)
Age: 5 to 6 years	0.049*** (0.004)	0.053*** (0.004)
Age: 7 years and older	0.035*** (0.006)	0.037*** (0.006)
Log of current size	-0.034*** (0.002)	
Firm size: 2 to 5 employees		-0.080*** (0.003)
Firm size: 6 or more employees		-0.088*** (0.003)
Log of start-up size	-	-
Start-up size: 2 to 5 employees	-	-
Start-up size: 6 or more employees	-	-
Innovator(binary)	-0.031** (0.005)	-0.029** (0.005)
Exporter(binary)	-0.027*** (0.004)	-0.030*** (0.004)
High-tech firm (binary)	-0.008* (0.005)	-0.008* (0.005)
Log-likelihood	-13747.452	-13590.145
Number of firms	17962	17962
Number of observations	17962	17962

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table D – Contrasts for the marginal effects on the hazard, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.050*** (0.002)	0.054*** (0.002)	0.036*** (0.003)	0.037*** (0.003)	0.047*** (0.003)	0.048*** (0.003)
Age: 5 to 6 years	0.008*** (0.003)	0.008*** (0.003)	-0.002 (0.004)	-0.001 (0.004)	0.001 (0.004)	0.002 (0.004)
Age: 7 years and older	-0.011*** (0.003)	-0.012*** (0.003)	-0.015*** (0.006)	-0.014** (0.006)	-0.015*** (0.006)	-0.017*** (0.007)
Log of current size	-0.029*** (0.001)				-0.060*** (0.002)	
Firm size: 2 to 5 employees		-0.074*** (0.003)				-0.116*** (0.005)
Firm size: 6 or more employees		-0.009*** (0.002)				-0.025*** (0.003)
Log of start-up size			-0.007*** (0.001)		0.037*** (0.002)	
Start-up size: 2 to 5 employees				-0.031*** (0.002)		0.027*** (0.003)
Start-up size: 6 or more employees				0.015*** (0.003)		0.007*** (0.007)
Innovator(binary)	-0.012** (0.004)	-0.012*** (0.004)	-0.029*** (0.005)	-0.028*** (0.006)	-0.028*** (0.005)	-0.027*** (0.005)
Exporter (binary)	-0.019*** (0.003)	-0.019*** (0.003)	-0.032*** (0.004)	-0.037*** (0.004)	-0.026*** (0.004)	-0.029*** (0.004)
High-tech firm (binary)	-0.012*** (0.004)	-0.014*** (0.003)	-0.001 (0.004)	-0.001 (0.005)	-0.004 (0.005)	-0.007 (0.005)
Log-likelihood	-16809.402	-16655.818	-14066.869	-14013.128	-13578.719	-13461.624
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	22198	22198	17962	17962	17962	17962

Statistics computed using only the last observation of each firm, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table E - Marginal effects on the hazard, for all observations of each firm, for high-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.031*** (0.008)	0.032*** (0.008)	0.018*** (0.009)	0.019*** (0.011)	0.027** (0.015)	0.028** (0.015)
Age: 5 to 6 years	0.048*** (0.009)	0.047*** (0.010)	0.019** (0.008)	0.021 (0.023)	0.034* (0.023)	0.034* (0.024)
Age: 7 years and older	0.046*** (0.011)	0.044*** (0.011)	0.013** (0.008)	0.015 (0.033)	0.029 (0.037)	0.029 (0.039)
Log of current size	-0.033*** (0.004)				-0.059*** (0.043)	
Firm size: 2 to 5 employees		-0.055*** (0.008)				-0.095*** (0.015)
Firm size: 6 or more employees		-0.079*** (0.008)				-0.124*** (0.015)
Log of start-up size			-0.012* (0.007)		0.031*** (0.007)	
Start-up size: 2 to 5 employees				-0.029*** (0.009)		0.028* (0.014)
Start-up size: 6 or more employees				-0.022* (0.012)		0.099*** (0.032)
Innovator(binary)	-0.049** (0.023)	-0.052** (0.023)	-0.096*** (0.033)	-0.097*** (0.033)	-0.081** (0.032)	-0.083*** (0.032)
Exporter(binary)	-0.009 (0.01)	-0.013 (0.01)	-0.039*** (0.014)	-0.039*** (0.014)	-0.021 (0.014)	-0.025* (0.014)
Log-likelihood	-1076.565	-1065.842	-948.079	-981.374	-951.688	-948.309
Number of firms	1443	1443	1227	1227	1227	1227
Number of observations	6269	6269	4324	4324	4324	4324

Statistics computed using the exponential model, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; ; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table F - Marginal effects on the hazard, for all observations of each firm, for low-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	0.052*** (0.002)	0.054*** (0.002)	0.038*** (0.003)	0.038*** (0.003)	0.048*** (0.003)	0.049*** (0.003)
Age: 5 to 6 years	0.060*** (0.003)	0.061*** (0.003)	0.037*** (0.004)	0.037*** (0.004)	0.049*** (0.004)	0.051*** (0.004)
Age: 7 years and older	0.048*** (0.003)	0.049*** (0.003)	0.021*** (0.006)	0.023*** (0.006)	0.031*** (0.006)	0.033*** (0.006)
Log of current size	-0.028*** (0.001)				-0.058*** (0.002)	
Firm size: 2 to 5 employees		-0.076*** (0.003)				-0.125*** (0.005)
Firm size: 6 or more employees		-0.084*** (0.003)				-0.148*** (0.006)
Log of start-up size			-0.007*** (0.001)		0.036*** (0.002)	
Start-up size: 2 to 5 employees				-0.031*** (0.003)		0.025*** (0.003)
Start-up size: 6 or more employees				-0.016*** (0.003)		0.091*** (0.007)
Innovator(binary)	-0.009** (0.004)	-0.009** (0.004)	-0.028*** (0.005)	-0.027*** (0.005)	-0.025*** (0.005)	-0.023*** (0.005)
Exporter(binary)	-0.019*** (0.003)	-0.022*** (0.003)	-0.038*** (0.004)	-0.039*** (0.004)	-0.025*** (0.004)	-0.029*** (0.004)
Log-likelihood	-16239.413	-15995.544	-14225.833	-14003.224	-13998.229	-13231.642
Number of firms	20755	20755	16735	16735	16735	16735
Number of observations	87048	87048	59159	59159	59159	59159

Statistics computed using the exponential model, using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table G - Marginal effects on the hazard for the models with interaction terms, for all observations of each firm, for all firms

	High-tech	**Low-tech**
Age: 2 to 4 years	0.031*** (0.007)	0.052*** (0.002)
Age: 5 to 6 years	0.043*** (0.009)	0.060*** (0.003)
Age: 7 years and older	0.038*** (0.011)	0.048*** (0.003)
Firm size: 2 to 5 employees	-0.059*** (0.009)	-0.075*** (0.003)
Firm size: 6 or more employees	-0.082*** (0.009)	-0.084*** (0.003)
Start-up size: 2 to 5 employees**	-0.030*** (0.009)	-0.031*** (0.003)
Start-up size: 6 or more employees**	-0.023 (0.013)	-0.016*** (0.003)
Innovator(binary)	-0.036*** (0.011)	-0.009** (0.004)
Exporter(binary)	-0.013 (0.008)	-0.017*** (0.003)
Log-likelihood	-15561.1	-15712.73
Number of firms	1443	20755
Number of observations	1443	20755

Statistics computed using the exponential model. All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%
**** For statistics considering start-up size, for high-tech firms the number of observations is of 4324 and the number of firms is of 1227, and for low-tech firms the number of observations is of 59159 and the number of firms is of 16735.

Table H - Hazard ratios for the exponential model, for all observations of each firm, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	2.376*** (0.098)	2.454*** (0.102)	1.553*** (0.052)	1.564*** (0.052)	1.777*** (0.059)	1.814*** (0.061)
Age: 5 to 6 years	2.592*** (0.115)	2.662*** (0.119)	1.529*** (0.069)	1.556*** (0.070)	1.791*** (0.081)	1.845*** (0.083)
Age: 7 years and older	2.288*** (0.110)	2.333*** (0.112)	1.307*** (0.092)	1.339*** (0.094)	1.513*** (0.106)	1.560*** (0.109)
Log of current size	0.699*** (0.009)				0.529 *** (0.011)	
Firm size: 2 to 5 employees		0.460*** (0.012)				0.375*** (0.014)
Firm size: 6 or more employees		0.393*** (0.011)				0.245*** (0.011)
Log of start-up size			0.924*** (0.014)		1.489*** (0.031)	
Start-up size: 2 to 5 employees				0.705*** (0.020)		1.345*** (0.048)
Start-up size: 6 or more employees				0.845*** (0.029)		2.246*** (0.105)
Innovator(binary)	0.869** (0.046)	0.869** (0.046)	0.712*** (0.041)	0.722*** (0.041)	0.742*** (0.042)	0.755*** (0.042)
Exporter(binary)	0.795*** (0.031)	0.760*** (0.029)	0.658*** (0.029)	0.649*** (0.028)	0.757*** (0.033)	0.731*** (0.032)
High-tech firm(binary)	0.864** (0.039)	0.839*** (0.038)	0.998 (0.050)	0.988 (0.049)	0.963 (0.048)	0.932 (0.046)
Log-likelihood	-16805.674	-16651.737	-14066.304	-14012.961	-13578.742	-13461.858
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	93317	93317	63483	63483	63483	63483

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table I - Hazard ratios for the exponential model, for all observations of each firm, for high-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	1.771*** (0.284)	1.781*** (0.285)	1.232*** (0.147)	1.242*** (0.148)	1.377*** (0.166)	1.383*** (0.166)
Age: 5 to 6 years	2.179*** (0.372)	2.159*** (0.369)	1.242** (0.210)	1.268** (0.214)	1.465** (0.248)	1.468** (0.248)
Age: 7 years and older	2.119*** (0.390)	2.074*** (0.382)	1.161* (0.292)	1.189* (0.298)	1.402* (0.354)	1.404* (0.356)
Log of current size	0.629*** (0.035)				0.525*** (0.042)	
Firm size: 2 to 5 employees		0.518*** (0.052)				0.404*** (0.058)
Firm size: 6 or more employees		0.309*** (0.045)				0.224*** (0.044)
Log of start-up size			0.883** (0.063)		1.404*** (0.101)	
Start-up size: 2 to 5 employees				0.714*** (0.079)		1.342** (0.189)
Start-up size: 6 or more employees				0.792* (0.128)		2.243* (0.424)
Innovator(binary)	0.505** (0.160)	0.485** (0.154)	0.351*** (0.125)	0.348*** (0.124)	0.416** (0.145)	0.404*** (0.141)
Exporter(binary)	0.876 (0.125)	0.829 (0.118)	0.658*** (0.100)	0.656*** (0.099)	0.799 (0.121)	0.764* (0.115)
Log-likelihood	-1066.565	-1065.842	-984.078	-1052.700	-981.374	-948.309
Number of firms	1443	1443	1227	1227	1227	1227
Number of observations	6269	6269	4324	4324	4324	4324

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table J - Hazard ratios for the exponential model, for all observations of each firm, for low-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age: 2 to 4 years	2.426*** (0.104)	2.509*** (0.108)	1.582*** (0.055)	1.593*** (0.055)	1.814*** (0.063)	1.850*** (0.065)
Age: 5 to 6 years	2.635*** (0.121)	2.711*** (0.125)	1.561*** (0.073)	1.588*** (0.074)	1.826*** (0.085)	1.878*** (0.088)
Age: 7 years and older	2.317*** (0.115)	2.368*** (0.118)	1.326*** (0.097)	1.358*** (0.099)	1.532*** (0.111)	1.573*** (0.114)
Log of current size	0.703*** (0.009)				0.529*** (0.012)	
Firm size: 2 to 5 employees		0.457*** (0.012)				0.359*** (0.014)
Firm size: 6 or more employees		0.396*** (0.012)				0.241*** (0.012)
Log of start-up size			0.925*** (0.014)		1.494*** (0.033)	
Start-up size: 2 to 5 employees				0.703*** (0.021)		1.332*** (0.049)
Start-up size: 6 or more employees				0.846*** (0.030)		2.241*** (0.109)
Innovator(binary)	0.890** (0.048)	0.892** (0.048)	0.732*** (0.042)	0.743*** (0.043)	0.758*** (0.043)	0.773*** (0.044)
Exporter(binary)	0.789*** (0.032)	0.756*** (0.031)	0.659*** (0.030)	0.648*** (0.030)	0.754*** (0.034)	0.727*** (0.033)
Log-likelihood	-15718.73	-15565.13	-13072.224	-13021.499	-12617.08	-12510.862
Number of firms	20755	20755	16735	16735	16735	16735
Number of observations	87048	87048	59159	59159	59159	59159

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table K - Hazard ratios for the Cox model, for all observations of each firm, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.694*** (0.009)				0.530*** (0.011)	
Firm size: 2 to 5 employees		0.454*** (0.012)				0.376*** (0.014)
Firm size: 6 or more employees		0.385*** (0.011)				0.245*** (0.011)
Log of start-up size			0.923*** (0.014)		1.482*** (0.031)	
Start-up size: 2 to 5 employees				0.703*** (0.020)		1.331*** (0.047)
Start-up size: 6 or more employees				0.842*** (0.029)		2.218*** (0.104)
Innovator(binary)	0.883** (0.048)	0.882** (0.047)	0.710*** (0.041)	0.719*** (0.041)	0.739*** (0.042)	0.752*** (0.042)
Exporter(binary)	0.795*** (0.031)	0.759*** (0.029)	0.657*** (0.029)	0.647*** (0.028)	0.757*** (0.033)	0.731*** (0.032)
High-tech firm(binary)	0.863** (0.039)	0.838*** (0.038)	0.998 (0.050)	0.988 (0.049)	0.963 (0.048)	0.932 (0.046)
Log-likelihood	-71362.726	-71206.07	-53220.786	-53166.825	-13578.742	-52612.723
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	93317	93317	63483	63483	63483	63483

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table L - Hazard ratios for the Cox model, for all observations of each firm, for high-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.622*** (0.035)				0.525*** (0.041)	
Firm size: 2 to 5 employees		0.511*** (0.051)				0.404*** (0.058)
Firm size: 6 or more employees		0.301*** (0.044)				0.224*** (0.044)
Log of start-up size			0.883** (0.063)		1.403*** (0.101)	
Start-up size: 2 to 5 employees				0.713*** (0.079)		1.339** (0.189)
Start-up size: 6 or more employees				0.791* (0.128)		2.237* (0.427)
Innovator(binary)	0.506** (0.161)	0.486** (0.155)	0.351*** (0.125)	0.348*** (0.124)	0.416** (0.144)	0.403*** (0.141)
Exporter(binary)	0.875 (0.125)	0.827 (0.118)	0.659*** (0.101)	0.657*** (0.100)	0.799 (0.121)	0.765* (0.116)
Log-likelihood	-3025.801	-3095.465	-2610.787	-2608.079	-2578.318	-2575.022
Number of firms	1443	1443	1227	1227	1227	1227
Number of observations	6269	6269	4324	4324	4324	4324

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table M - Hazard ratios for the Cox model, for all observations of each firm, for low-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.697*** (0.009)				0.530*** (0.012)	
Firm size: 2 to 5 employees		0.451*** (0.012)				0.359*** (0.013)
Firm size: 6 or more employees		0.388*** (0.012)				0.242*** (0.012)
Log of start-up size			0.924*** (0.014)		1.485*** (0.032)	
Start-up size: 2 to 5 employees				0.701*** (0.021)		1.318*** (0.049)
Start-up size: 6 or more employees				0.843*** (0.030)		2.210*** (0.108)
Innovator(binary)	0.905** (0.049)	0.906** (0.049)	0.730*** (0.042)	0.741*** (0.043)	0.755*** (0.043)	0.769*** (0.044)
Exporter(binary)	0.789*** (0.032)	0.754*** (0.031)	0.658*** (0.030)	0.647*** (0.030)	0.753*** (0.034)	0.726*** (0.033)
Log-likelihood	-66456.181	-66299.827	-49145.014	-49093.675	-48687.38	-48580.272
Number of firms	20755	20755	16735	16735	16735	16735
Number of observations	87048	87048	59159	59159	59159	59159

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table N - Hazard ratios for the Weibull model, for all observations of each firm, for all firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.666*** (0.009)				0.526*** (0.011)	
Firm size: 2 to 5 employees		0.434*** (0.012)				0.377*** (0.013)
Firm size: 6 or more employees		0.348*** (0.011)				0.238*** (0.009)
Log of start-up size			0.889*** (0.014)		1.384*** (0.028)	
Start-up size: 2 to 5 employees				0.655*** (0.021)		1.152*** (0.041)
Start-up size: 6 or more employees				0.773*** (0.029)		1.899*** (0.087)
Innovator(binary)	1.029 (0.057)	1.023 (0.057)	0.717*** (0.042)	0.725*** (0.042)	0.749*** (0.043)	0.758*** (0.044)
Exporter(binary)	0.810*** (0.033)	0.765*** (0.031)	0.612*** (0.028)	0.599*** (0.028)	0.729*** (0.034)	0.693*** (0.032)
High-tech firm(binary)	0.846*** (0.041)	0.819*** (0.040)	0.994 (0.055)	0.983 (0.055)	0.954 (0.053)	0.917 (0.051)
Log-likelihood	-15984.613	-15834.105	-13234.707	-13164.924	-12641.303	-12498.580
Number of firms	22198	22198	17962	17962	17962	17962
Number of observations	93317	93317	63483	63483	63483	63483

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators; low-tech firms). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table O - Hazard ratios for the Weibull Model, for all observations of each firm, for high-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.593*** (0.034)				0.457*** (0.037)	
Firm size: 2 to 5 employees		0.486*** (0.051)				0.337*** (0.044)
Firm size: 6 or more employees		0.265*** (0.039)				0.188*** (0.035)
Log of start-up size			0.684*** (0.053)		1.214** (0.097)	
Start-up size: 2 to 5 employees				0.481*** (0.053)		1.016* (0.144)
Start-up size: 6 or more employees				0.528*** (0.092)		1.686** (0.317)
Innovator(binary)	0.538** (0.176)	0.513** (0.169)	0.279*** (0.103)	0.279*** (0.103)	0.336*** (0.122)	0.331*** (0.121)
Exporter(binary)	0.911 (0.134)	0.853 (0.126)	0.607*** (0.095)	0.597*** (0.094)	0.776* (0.119)	0.719** (0.111)
Log-likelihood	-1007.553	-1008.597	-1008.538	-997.990	-956.308	-944.903
Number of firms	1443	1443	1227	1227	1227	1227
Number of observations	6269	6269	4324	4324	4324	4324

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table P - Hazard ratios for the Weibull Model, for all observations of each firm, for low-tech firms

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log of current size	0.669*** (0.009)				0.527*** (0.011)	
Firm size: 2 to 5 employees		0.431*** (0.012)				0.358*** (0.013)
Firm size: 6 or more employees		0.352*** (0.111)				0.236*** (0.011)
Log of start-up size			0.891*** (0.015)		1.385*** (0.029)	
Start-up size: 2 to 5 employees				0.654*** (0.021)		1.141*** (0.042)
Start-up size: 6 or more employees				0.774*** (0.030)		1.875*** (0.088)
Innovator(binary)	1.061 (0.060)	1.057 (0.060)	0.739*** (0.044)	0.748*** (0.045)	0.767*** (0.045)	0.778*** (0.046)
Exporter(binary)	0.802*** (0.034)	0.759*** (0.032)	0.613*** (0.029)	0.599*** (0.029)	0.726*** (0.035)	0.689*** (0.033)
Log-likelihood	-14952.195	-14800.879	-12289.121	-12223.248	-11738.266	-11609.576
Number of firms	20755	20755	16735	16735	16735	16735
Number of observations	87048	87048	59159	59159	59159	59159

All estimations control for rate of yearly change of GDP, unemployment rate per year and region. For categorical variables the base levels are not presented (age = 1 year; current size = 1 employee; start-up size = 1 employee; non-exporters; non-innovators). Standard errors presented in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%