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Firm Dynamics in the Knowledge-Intensive Services Industry

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Abstract

The service industry has become the main contributor for economic growth and employment in Portugal and worldwide. Since we are moving towards a knowledge-based economy, it is of the utmost importance to research how knowledge-intensity has an influence on the dynamic of entries and closures in the service market. We analyse firm dynamics in the service industry, focusing on the determinants of firm survival, while comparing knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS), and using the *Integrated Business Account System* (SCIE) data-set from 2007 to 2015. We apply a semi-parametric duration model (piecewise-constant exponential model), and find that: age, size and start-up size have a negative effect in hazard of exit; innovators have lower hazard of exit than non-innovators; exporters have lower hazard of exit than non-exporters; firms with positive growth rate, in terms of sales per employee, have lower hazard of exit than firms with negative growth rate; and KIS firms have lower hazard of exit than LKIS firms. We also characterise the different impact of these factors between KIS firms and LKIS firms, where we find that their effect is more intense in LKIS firms hazard of exit than KIS firms hazard of exit.

Keywords: Firm dynamics, Firm survival, Service industry, Knowledge-intensive services, Innovation.

Resumo

O setor de serviços tornou-se o principal contribuinte para o crescimento económico e empregabilidade em Portugal e no mundo. Como estamos a caminhar cada vez mais para uma economia baseada no conhecimento, é de extrema importância investigar como é que a intensidade de conhecimento influencia entradas e saídas de empresas no mercado de serviços. Analisamos a dinâmica empresarial no setor de serviços, com foco nos determinantes de sobrevivência, comparando serviços intensivos em conhecimento (KIS) com serviços menos intensivos em conhecimento (LKIS) e usando como fonte de informação o *Sistema de Contas Integradas das Empresas* (SCIE) no período de 2007 a 2015. Aplicamos um modelo de duração semi-paramétrico (*piecewise-constant exponential model*) e constatamos que: idade, dimensão e dimensão inicial têm um efeito negativo na *hazard* (risco) de saída; empresas inovadoras têm menor *hazard* de saída do que empresas não-inovadoras; empresas exportadoras têm menor *hazard* de saída do que empresas não-exportadoras; empresas com taxas de crescimento positivas, em termos de vendas por trabalhador, têm menor *hazard* de saída do que empresas com taxas de crescimento negativas; e empresas KIS têm menor *hazard* de saída do que empresas LKIS. Também caracterizamos o impacto destes fatores em empresas KIS e empresas LKIS e constatamos que o seu efeito é mais intenso na *hazard* de saída de empresas LKIS do que na *hazard* de saída de empresas KIS.

Palavras-Chave: Dinâmica de empresas, Sobrevivência de empresas, Indústria de serviços, Serviços intensivos em conhecimento, Inovação.

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Chapter 1

Introduction

We are progressively moving towards a knowledge-based economy, where technology and knowledge are key production factors to value creation. The Portuguese economy has been gradually shifting from an extensive economic model of growth, that relied on unqualified work and low wages, to an intensive economic model of growth, where it employs technology, innovation and knowledge management, in order to improve productivity and human resources qualification. This applies for both the tertiary (or services) sector and the secondary (or manufacturing) sector, since they are slowly advancing towards a technological convergence, i.e., the secondary sector is resorting to service products related to manufacturing (e.g., integrated management systems, engineering, product conception), and the tertiary sector is employing products more associated to manufacturing (e.g., Information Technology, Automation, Machine Learning) (Amaral, 2008).

With this technological convergence and growing knowledge demand, firms that produce knowledge are becoming more relevant to the global economy. The service sector rise has extended to knowledge-based firms, having a key role in the development of innovative activities and economic growth. Innovation and human capital are gaining importance in the knowledge-based economy, considering that companies need both to create value and, ultimately, a sustainable competitive advantage (OECD, 1996). Consequently, the tertiary sector has expanded into a significant share of the total market of firms in Portugal, representing approximately 70% of the total employment in Portugal, where the weight of intangible goods on international trade has increased as well (Amaral, 2008).

Under these rapid changes, external factors also influence firm performance in a knowledge-based economy. After years of expansion driven by credit in the non-transactional sector and decline in exports, Portugal entered into a deep recession in 2011 that led to a rise of the unemployment rate and public debt (OECD, 2014). Even with a slow economic recovery and recent reduction of the corporate debt burden, these macroeconomic conditions had a strong impact in the economy. For these reasons, studies of firm dynamics in the service industry are of the utmost importance to understand the main factors of entries and exits in the market and how companies may survive in this new competitive environment.

1.1 Research Tasks

We find studies that characterise knowledge-intensive firms, some of them with a special focus on knowledge-intensive business firms, due to their importance as knowledge intermediaries and innovation agents of economic growth. However, few of these studies discuss which factors may support a longer stay in the market for this type of firms. Therefore, this thesis main goal is to fill this gap and contribute for a better understanding of the main factors for knowledge-intensive service (KIS) and less knowledge-intensive service (LKIS) firm survival, and how differently these factors affect each type of service firm. Thus, the first main research task of this thesis is to identify which factors may influence firm survival in the service industry. The second task is to evaluate how differently these factors influence the firm survival of KIS and LKIS firms.

From the literature review, one finds that age and size are unquestionable variables that explain firm dynamics, having a negative correlation with firm growth and survival (Dunne and Hughes, 1994; Dunne et al., 1988; Evans, 1987a). Moreover, we may not deny the considerable influence of firm size in our study, since the majority of firms in the Portuguese economy are micro firms, which are the most vulnerable to closure (Dunne and Hughes, 1994; Evans, 1987a; Fritsch et al., 2006). It is also known the positive influence of decisions like exporting or innovating in the post-entry firm performance and survival. Several studies suggest that exporters are better performers than non-exporters, and that innovation has also a positive impact on firm performance and profitability (Audretsch, 1991; Bernard et al., 1995; Mansfield, 1962). There is also evidences that improvements in firm's performance and growth rate may increase the chances of survival (Audretsch, 1995). In line with the literature review findings, we develop a set of hypotheses stating that the following variables have a negative impact on hazards of exit: type of industry (KIS or LKIS), age, size, start-up size, innovation, exports and growth rate. Further on, we also assess the impact of these variables in interaction with knowledge-intensity through a set of sub-hypotheses, implying a different impact of these variables in KIS and LKIS firms.

1.2 Methodology and Results

In order to provide meaningful insights regarding the major factors of firm survival and further effect on KIS and LKIS firms, we consider survival analysis methods due to its adequacy for the study. We use the Integrated Business Accounts System data-set (*Sistema de Contas Integradas das Empresas — SCIE*), provided by Statistics Portugal (*Instituto Nacional de Estatistica* — INE). As a preliminary analysis, we test our hypotheses through a non-parametric approach, namely, Kaplan-Meier survival rates estimates. Afterwards, we apply a semi-parametric method, the piecewise-constant exponential model, where we compute the corresponding average marginal effects of each determinant with the following results: KIS firms have lower hazard of exit than LKIS firms; age, size, start-up size, innovation, export and growth rate have a negative impact on hazard of exit; and the effect of age, size, start-up size, innovation, export and growth rate is more intense on LKIS firms hazard rates than KIS firms hazard rates.

With these results, we examine all main hypotheses and sub-hypotheses. We conclude that the distinct impact observed between LKIS and KIS hazard rates might be caused by their specific characteristics such as the degree of service customisation and education level of the workforce. We suggest for future work to explore alternative survival models for more robust results, and to study the subgroups within KIS and LKIS sectors.

1.3 Structure of the Document

This dissertation is organised as follows. In Chapter 2, we present a review of the most relevant literature on firm dynamics, focusing on firm growth, firm survival and knowledge-intensity. In Chapter 3, we introduce and characterise the data-set. In Chapter 4, we describe our hypotheses, preliminary analysis and methodology. In Chapter 5 we present the final results, discussion and limitations of our survival analysis. Finally, in Chapter 6, we present a summary of the document and relevant conclusions.

Chapter 2

Literature Review

This Chapter presents a review of the literature on the most relevant factors that influence a firm's performance (mostly firm survival and growth), and also the main characteristics of the service industry, focusing on knowledge-intensity. Since there is an intangibility nature inherent to the service sector, which makes it more attached and dependent on the characteristics of the workforce, we will mention some findings related to human capital. While having this in mind, this study will focus mainly on internal factors, firm's strategy and the characteristics that influence the duration of services firms.

2.1 Firm Survival and Growth Determinants

Firm growth and firm survival are subjects widely studied due to its economic importance. It is plausible to say that without growth, or in a stagnated economy, firms tend to leave the market sooner than they should. Most firms that emerge in the economy never get to reach maturity — hazard rates of closure tend to increase during the first years and decrease afterwards (Mata and Portugal, 1999; Wagner, 1994). Hence, there is a need to settle which factors affect firm survival and growth and, for the purpose of this work, understand their effects on the service industry. Most studies on firm survival and growth found in the literature are based on the manufacturing sector, however, we found them suitable for services as well. Factors such as the characteristics of the demand and technology, market size, growth rates, market structure, technological regime and life cycle are proven determinants of firm survival at the industry level (Agarwal and Gort, 1996; Audretsch, 1991, 1995; Mata et al., 1995; Suárez and Utterback, 1995). Furthermore, age and size are two factors extensively researched, with an influence in firm survival and growth. This section analyses theoretical findings and evidences that support the importance of these variables, along with financial factors, to explain firm growth. Moreover, several other major factors, such as innovation, exports or education level of the workforce can also be applied to the service sector — we will discuss these in the following sub-sections.

2.1.1 Age, Size and Start-up Size

Several studies present findings that exhibit the importance of age and size on firm survival and growth. According to Evans (1987a) and Dunne and Hughes (1994), there is a negative correlation be-

tween firm growth and age, suggesting that younger firms grow faster than older firms. More specifically, studies indicate that older firms have a lower growth variability than new firms, where younger firms have more volatile performances and growth rates that decrease over time (Evans, 1987a; Mansfield, 1962). Moreover, Audretsch (1995) argues that new firms may experience high growth rates if they can adjust and offer a viable product to the market. As consequence, it will improve their prospects of survival.

Initially, there was a more conventional perception that firm growth and size were not related. According to Gibrat's law, growth rate and size were independent, with a stable and lognormal distribution (Gibrat, 1931). Later, more findings emerged with evidences that discarded this law, indicating that firm growth decreases with firm size (Evans, 1987a), with higher and more variable growth rates on smaller firms than larger firms (Mansfield 1962). Cabral and Mata (2003) support this trend, showing that financial constraints have a vast influence on the firm's investment decisions, with a greater effect on younger firms. Besides, this relationship between firm growth and size is non-linear and varies over the size distribution of firms (Evans, 1987b). According to Jovanovic (1982), this is caused by the learning process that firms go through regarding their true efficiency, as they operate in the industry. This is referred as the theory of "noisy" selection, which says that "(...) efficient firms grow and survive (...)", while "(...) inefficient firms decline and fail". However, Cabral and Mata (2003) found no relationship between the selection effect and the evolution of the firm size distribution.

The likelihood of survival increases with firm size and age where, consequently, smaller and younger companies have higher failure rates (Dunne and Hughes, 1994; Evans, 1987a). According to Fritsch et al. (2006), high vulnerability to failure of new firms is mostly due to the initial period without profit, and eventual problems on setting an organisational structure. Except for takeovers, a firm's death is also preceded by slow growth, and it has more impact on smaller companies than larger companies (Dunne and Hughes, 1994). Empirical work from Dunne et al. (1988) shows that firms that manage to survive tend to become larger in the subsequent years than the upcoming new-firm entrants. However, high exit rates of firms from a certain cohort may overpower the effect of size increase, leading to a market share decrease as the cohort ages. Dunne et al. (1988) also found that entry and closure rates are positively correlated across industries but are negatively correlated when specific industry effects are removed.

As mentioned before, Jovanovic (1982) argues that the main reason for survival is related to the firm's awareness of their efficiency, and those that fail in this task will most likely not survive. This efficiency awareness is achieved over time as the firm becomes more mature, where they gained knowledge regarding their cost structures and efficiency levels (Dunne et al., 1988; Jovanovic, 1982). As the likelihood of survival for new entrants tends to be lower in industries characterised by high minimum efficient size (Fritsch et al., 2006), not meeting the requirements of the industry may be an obstacle to survival.

Start-up size also plays an important role. Even though size is inversely correlated with growth, having a significant importance to survival on early stages (Evans, 1987a; Jovanovic, 1982), further empirical studies shows a positive effect of start-up size on survival. According to Mata and Portugal (1994), survival is higher among firms that initiated their activity with a large start-up size, since it indicates a greater expectation of success. Also, Mata and Portugal (1994) have found that firms that enter the market in larger scale and multiple establishments are more likely to survive longer. Moreover,

Brüderl et al. (1992) argue that, even though being small can prevent possible ”financial disaster” (related to higher financial requirements and risk by larger firms), it also increases the exposure to failure. This study proposes that each industry have a minimum start-up size, for which a newly formed firm should not start below that level, in order to succeed at minimum risk. But this requirement may be different for some industries, along with the importance of start-up size in the long term. According to Agarwal and Audretsch (2001), the advantage of entering the market at large scale may vary with the competitive environment where the firm operates, such as product life cycle and technological intensity, and it dissipates over the years. They suggest that it is beneficial to enter a low-tech industry in large scale. However, large size does not provide any significant advantage while entering into a mature or high-tech industry. The main justification lies on the fact that, as oppose to what happen in initial stages, firms are not so compelled to compete for a viable product in order to survive. Instead, small firms are more interested in occupying a strategic niche that allows them to compete and survive in mature and/or technological industry. In this case, it is more important to seek an niche marketing opportunity than having large size and undertake high research and development (R&D) expenses.

2.1.2 Financial Factors

Financial factors may influence the firm's growth rate, having a higher effect on younger and smaller firms. Headd (2003) argues that when firms have more resources, i.e., are larger and have access to better financing tools, they have higher prospects of survival. Huynh and Petrunia (2010) support this argument: they found that firm growth increases with the firm's initial asset level, suggesting that companies that start with a substantial budget will have fewer constraints, which may encourage growth. According to Cabral and Mata (2003), some firms are small due to financial constraints while others stay small for efficiency purposes. When financial constraints are surpassed, firms will grow to an optimal size, as discussed at the beginning of Section 2.1.1. Furthermore, small firms are characterised by paying less dividends, taking on more debt and investing more, being more sensitive to cash flows (Cooley and Quadrini, 2001). In less financially developed economies, small firms grow at a faster pace with lower debt than large firms. As the financial development improves, this growth gap starts to decrease as the leverage difference increases (Arellano et al., 2012).

Brüderl et al. (1992) state that having sizeable financial funds at start-up improves the likelihood of new firm's survival, because these funds may help dealing with random external causes, while accelerating people's engagement on their business. The source of financing may be different either for large or small firms. Larger firms have more access to external financing, while smaller firms' investment may come from more informal sources such as family and friends (Beck and Demirguc-Kunt, 2006). Financing small firms implies more risk for external and financial institutions, that can turn into higher interests from loans, which might be an unbearable additional expense to these firms. For these reasons, financial and legal matters constraint firm growth, but more intensively for smaller firms than for larger firms (Beck and Demirguc-Kunt, 2006). Additionally, large firms have the upper hand on collecting more capital while small firms will, more likely, have smaller overhead costs and resource requirements.

2.1.3 Innovation

We may consider innovation (be it product or process based) as a path to generate or acquire new knowledge and competencies, to cope with a progressing technology-based economy (Hipp and Grupp, 2005). The importance of innovation is clear in both the service and manufacturing sectors. While in manufacturing it is mostly associated with new technology or innovative products, service innovation may be achieved through, for instance, new information technology to increase process efficiency (Miozzo et al., 2003), or process innovation. For these reasons, innovation is a powerful explanatory factor, that can justify performance differences observed between firms.

Empirical studies have found that innovation has a significant and positive impact on firm's performance and profitability, ultimately translated into a positive effect on the probability of survival (Audretsch, 1991, 1995; Mansfield, 1962). This is particularly true in small and young firms: since they are more exposed to the risk of leaving the market sooner than expected, they benefit the most of innovation to survive, while dealing with the liability of newness (Cefis and Marsili, 2005, 2006). Nonetheless, the risk-reward deal that comes from innovation is much higher for young firms, and its "innovation premium" increases their chance of surviving, when compared with non-innovative firms (Cefis and Marsili, 2006). However, Banbury and Mitchell (1995) argue that mature and well established firms benefit equally from innovation, since innovative activities allows them to cope with new and disruptive technologies while improving their existing capabilities, in order to stay competitive in the market.

Studies has shown that R&D investment towards innovation has a greater unstable effect on young firms than older firms. Coad et al. (2016) suggest that innovation may be riskier for younger firms, since the returns from R&D may be more unpredictable in the early stages of the firm but become more predictable over time. Older firms undertake safe incremental innovation moves, rapidly spotting projects that will probably fail, or have a diversified portfolio of projects, to reduce the uncertainty related with the totality of R&D investments.

Moreover, young firms that are capable to adjust to the environmental requirements and provide a viable product, have greater prospects of survival. This ability can be an important strategic instrument to cope with possible scale and size disadvantages while having an opportunity to enter small scale market niches (Audretsch, 1995). In fact, the entry of young firms may serve as a mean to introduce innovation into an industry (Geroski, 1995), in order to overcome possible barriers of entry or to create new small markets. However, solely introducing innovation in form of product or process may not be enough to improve the probability of survival — the characteristics of the new product must match the need of the market (Geroski, 1995). Moreover, innovation must be combined with firm specific capabilities to ensure a proper and efficient use of innovation (Cefis and Marsili, 2005).

According to Audretsch (1995), the importance of innovation on firm's survival is also directly linked to the type of industry. The survival probability of new entrants in highly innovative industries is lower comparing to industries where innovation is less important. This aspect can be related to how influential are some generic industry characteristics on firm's survival, such as structural barriers, scale economies or even product differentiation. In fact, we can consider that entry barriers, and the industry structure

that lead into these barriers, are obstacles for new firms to survive longer in the market (Geroski, 1995). However, according to Audretsch (1995), these barriers may have a temporary effect, namely, its impact becomes weaker over time, while entrant firms gains experience in the industry. Indeed, Cefis and Marsili (2005) argues that innovation alone does not improve the probability of survival for science-based firms since, as mentioned before, it must be aligned with the firm's capabilities, in order to be efficiently exploited. As for the type of innovation, according to Cefis and Marsili (2005), process innovation has a significant role on creating competitive advantage and, therefore, improve the likelihood of survival. Product innovation also enhances the probability of survival, but only combined with process innovation. However, this could vary since, as Cefis and Marsili (2005) suggested, the role of product and process innovation may be different over the life cycle of the industry. In general, product innovation is riskier and may expose young firms to failure at early age, whereas process innovation can turn into a safe competitive driver, increasing the prospectives of survival (Colombelli et al., 2016).

Audretsch (1991) argue that innovative firms will have higher growth rates on sale at some point of their duration, while firms that are not innovative enough will have lower growth rates and, therefore, are more susceptible to closure. Factors like technology conditions, knowledge or business cycle can affect how firms implement innovative processes, which, consequently, affect the survival likelihood, even if these factors vary from industry to industry (Mata and Portugal, 1999; Audretsch, 1991).

2.1.4 Exports

From previous findings, we may conclude that it is crucial for a firm to have a certain level of growth to survive its competitive environment. One possible solution is to expand their business abroad. Indeed, according to Bernard et al. (1995), exporters have a positive impact for the economy, being more productive, profitable and more competitive than non-exporters.

International trade may be triggered by differences in factors of production such as technical capability, endowments and the structure of production (Bernard et al., 1995; Wagner, 1995). For the service industry, in general, international trade is triggered by differences on expertise and knowledge, since exporting is one form of earning profits through the firm's specific knowledge (Wagner, 1995). However, different factors such as when, where and how much to export are related with the cost-benefit trade, the price of the product, possible economies of scale, among others, which may be a deciding factor on exploring international trade (Hirsch and Lev, 1971).

Export performance can be highly influenced by the firm size. Firstly, the likelihood of a firm being an exporter increases with firm size, related with a lower risk associated with exports, in comparison with smaller firms (Hirsch and Adar, 1974; Wagner, 1995). This is related with the advantages of economies of scale in production that large firms have or, for instance, with the lower cost of foreign marketing per product. On the other hand, smaller firms can also benefit from exporting, since it can be an escape to eventual issues from small domestic market (Hirsch and Lev, 1971), such as underperformance, local demand knock-out or even economic crisis.

In terms of employment growth and size, exporters perform better than non-exporters, either in manufacturing or services, being more productive than non-exporters (Bernard et al., 1995). They become

larger and more productive. Therefore, they provide better prospects of employment and higher salaries, thus the economic importance of exports for growth and survival. However, there is a causality issue while studying exportation since, according to Wagner (1995), exports may lead to growth but, at the same time, its size may lead to invest more in exports. This detail will be considered while analysing this factor in our models.

2.1.5 Human Capital of the Founder and the Team

The general attributes of the firm's workforce and its managerial staff can determine the success of a company. Collectively, education level and labour market experience tends to have a positive impact on firm's survival (Baptista et al., 2012). When it comes to the general workforce, having a high percentage of experienced workers increases the probability of survival (Brüderl et al., 1992). Also, firms with a highly educated workforce tends to present higher sales.

Another aspect to consider in the organisational success of a firm, and consequently its survival, is the individual characteristics of its founder. Higher levels of education can provide the capabilities required for problem-solving and decision-making — critical features for a founder in the firm's early stages — and, therefore, have a positive impact on the survival of knowledge-based companies (Baptista et al., 2012). Moreover, according to Brüderl et al. (1992), when it comes to productivity, founders with a greater human capital will have less uncertainty regarding their efficiency. Additionally, the founder's education can be a complementary decision factor for the customer in the service sector, along with global characteristics of its task force, since the quality of the service is not easily assessed (Brüderl et al., 1992). This finding is also accurate to the reversed scenario. For example, banks can use it as a screening criterion while evaluating firms for future funding where, in this particular case, the client is the founder.

According to Brüderl et al. (1992), there are different opinions regarding the value of the founder's features, more specifically coming from modern sociology, that overlooks the importance of the individual, and rather emphasises the value of organisations' structural characteristics and environmental conditions. However, there is evidence that prior experience and knowledge of the industry-specific before starting the business have a strong effect on firm survival. Baptista et al. (2012) suggest that firms founded by more educated individuals have a higher likelihood to perform better and, therefore, survive. This is clearer among small firm founders, where early experience and knowledge on starting a business and industry-specific determinants plays a greater role. Jovanovic (1982) argues that firms learn about their efficiency and abilities over time, so this early experience from the founder can provide some leverage over the competition. This experience can influence the decisions of the founder regarding, e.g., what markets to serve, the attributes of the product, resource allocation or even firm's organisation in terms of internal and external activities (Pakes and Ericson, 1998).

Furthermore, founders with higher education are more likely to be innovators, with higher chances of obtaining external financing to pull the initial phase of the firm (Baptista et al., 2012). As aforementioned, innovation has a positive role on firm survival. In fact, Dunne and Hughes (1994) suggests that the instability of growth rate observed in small firms, while comparing with more stable growth on larger

firms, most certainly is caused by lack of experience and management skills. This argument reinforces the relevance of the founder and workforce's experience and knowledge.

2.2 Knowledge and the Service Industry

Over the last years, the service sector has gained a relevant role on the economy, where the current trend is a move into a knowledge-intensive economy, i.e., economies directly related to the production, distribution and use of knowledge and information (OECD, 1996). In this context, human capital and knowledge-intensive services firms play an important role as "knowledge intermediaries" (Hipp and Grupp, 2005). The increase of these intermediaries indicates a growing demand for knowledge input from organisations to deal with a constantly changing environment, either from technology or social conditions (Miles, 2005). As consequence, innovative activities are gaining more relevance in the service sector, where they are an important motivating force of growth and change (Hipp and Grupp, 2005). Thus, given the context of our study, we must analyse the service sector more closely, in order to align the previous discussion with the main purpose of this thesis.

2.2.1 Main Characteristics of Services

We may define service as "any act or performance that one party can offer to another, that is essentially intangible and does not result in the ownership of anything " (Kotler et al., 2000, p. 356). Thus, scholars have often emphasize their differences from manufacturing, more specifically related to their operations, competitiveness and innovation (Tether and Hipp, 2002). The service sector is mainly characterised by the following features (Tether and Hipp, 2002; Miles, 2008; Hipp and Grupp, 2005).

- **Intangibility and perishability** - Services are consumed in place and time, difficult to store, and may imply high levels of communication flows, often through information technologies (ICT). They may act on people, by transforming their physical and/or emotional state (e.g., transportation, entertainment), by creating, providing or processing information.
- **Heterogeneity and uniqueness** - There is a close interaction between production and consumption, being sometimes highly tailored to a specific client or situation, as opposed to being standardised. Also, it can be hard for the company to change the services it provides, since it often lacks autonomy over production, a fact that is more typical in manufacturing than services.
- **Process orientation and interactivity** - Services may sometimes require the interaction or even active participation of the client. Moreover, there is a closer relationship between what is produced and its process than in the manufacturing sector. This closeness can make it hard to distinguish product from process innovation in services.
- **Critical role of organizational factors and coordination of activities** - Traditional services are usually provided in the same physical space and tends to be small scale and local. However, service firms that act on information does not require proximity from the user. Hence, there is a close relationship between the technologies employed and the organizational form of the service, with implications for the process and nature of the service provided.
- **Weak intellectual property protection** - Usually, successful service concepts that are not de-

pendable of deep procedural or organizational changes can be rapidly imitable by competitors, due to poor existing intellectual property rights. As consequence, some service firms concentrate their innovation efforts to processes and back-office functions. However, the nature and quality of the service is still the primary source of competitiveness for some service firms, especially if they are complex and/or require input from the client.

- **Human capital key role** - Services rely deeply on people, particularly of their skills and knowledge. In fact, these knowledge and skills that are embodied in individuals are imperative to production of services, rather than physical plants or equipment. For these reasons, human capital has an important role in creating value in services, being responsible for its evolution and quality.

2.2.2 Knowledge-Intensive and Less Knowledge-Intensive Service Firms

With the rise of distribution and utilisation of knowledge, firms related to the production of knowledge started to gain significant relevance in the economy, playing a role of knowledge intermediaries. We may define knowledge-intensity as "the extent to which a service activity requires highly skilled service operatives who exercise professional or technical capabilities to produce situation specific results" (Miles, 2008, p. 117). From this definition results the classification of firms according to knowledge-intensity, where their economic activities produce/utilise knowledge, by combining knowledge from different sources.

From recent literature, we may identify three main definitions involving service firms that are researched by scholars: knowledge-intensive activities (KIA), knowledge-intensive service firms (KIS) and knowledge-intensive business services firms (KIBS). The last two types may be treated as synonyms, however, they have subtle differences (Hipp and Grupp, 2005; Tether and Hipp, 2002). KIS is described as any service that implies the provision or production of knowledge, whereas KIBS is more oriented to organizations rather than consumers, therefore, it excludes educational, information or cultural activities (Wood, 2003). KIA may involve services activities with, for instance, manufacturing firms (e.g., management consultancy). Even though a company may not be considered a KIS firm, it might resort to internal KIA with, for example, business units or departments within the organisation providing services to other business units. Even networks identified in clusters, including suppliers customers and firms within the same industry, may be considered KIA without having a KIBS or KIS firms involved (OECD, 2006).

According to a survey conducted by Tether and Hipp (2002) to German firms in mid-1990s, service firms competitiveness lies on quality and flexibility on meeting users' needs, rather than price, where a large proportion of knowledge-intensive firm's income being earned from customized services. More technical and knowledge-intensive firms tend to invest less in new machinery and equipment per employee. Instead, these services spend more on information communication technologies (ICT) than other services in general, since they rely on knowledge and expertise of their workforce, hardly replaceable by machines and equipment. Also, Tether and Hipp (2002) suggest that less knowledge-intensive service firms invest more in non-technical ICT technologies, related with their provision of standard services, than knowledge-intensive firms. This is often a strategy, associated with routinisation and economies of scale, that allows these firms to substitute "high-skill-high-cost" labour for "low-skill-low-cost" labour.

The research found in recent literature focuses more on knowledge-intensive business services (KIBS), which excludes non-business activities related with public education and certain administrative services, more oriented to B2B, due to their importance as source of important new technologies to the economy, ”high-quality-high-wage” employment and future wealth creation (Tether and Hipp, 2002). According to Miles (2005), there are two types of KIBS: those related with more traditional services, such as accountancy, and legal services, often referred as traditional professional KIBS (p-KIBS); and those linked with technology, along with the production of new technology such as engineering services and computer services, referred as technological-based KIBS (t-KIBS).

Due to the specific characteristics from these firms, KIBS requires a closer supplier user interaction, as they act as a knowledge source for their clients. It involves an active process that conveys knowledge, knowledge exchange and the application of expertise to knowledge, directly related to the needs and complementary expertise used by the client. This sort of ”service content” provided by KIBS is frequently referred as consultancy, which usually involves KIA that offer expertise in management and administration, production, research, information and communications, and marketing (Muller and Zenker, 2001; Wood, 2003). This type of activities, also described as ”professional services”, rely on the skills and accreditation of individuals, along with the establishment of client trust, reinforcing the importance of human capital on the KIS industry. The rapid growth of KIBS over the years have improved the process of innovation and contribute to national and regional development (Wood, 2003; Muller and Zenker, 2001).

2.2.3 The Role of Knowledge-Intensity and Innovation in the Service Industry

In the last 200 years, classical economical models held work and capital as the only explanatory production factors to economic growth (Amaral, 2008). Nowadays, with the service sector globally dominating the share of employment, knowledge and technology have also become relevant production factors. Gradually, we have been evolving into a knowledge-based economy, i.e., where competitiveness lays on activities linked to the production and process of knowledge and information (OECD, 1996). Currently, the value of high-tech companies or knowledge-based companies not only lies in their physical assets but also intangible assets, such as, e.g., patents and know-how. Moreover, the trade of intangible goods has a significant weight on international trade. As consequence, firms started to heavily resort to innovation, in order to improve their survival capabilities, and compete in a sustainable way given that, in opposition to the traditional economy, the knowledge-based economy is an economy not of scarcity but of prosperity since information and knowledge can be shared, while scarce tangible resources may not (Amaral, 2008; OECD, 1996).

Several studies indicate that knowledge-intensive service activities have a significant role in innovation process and development. According to a study from OECD (2006), there are some distinctions that can be made between different types of knowledge, in order to facilitate economic analysis: *know-what*, related to facts; *know-why*, that refers to scientific knowledge; *know-how*, associated to skills or the capability to do something; and *know-who*, that involves information and the formation of social relationships which ”make it possible to get access to experts and use their knowledge efficiently”. These four kinds of knowledge can be learn using different channels: *know-what* and *know-why* can be achieved

through books, lectures and databases, the other two types are obtainable in practical experience. The combination of these types of knowledge are the basis to the creation of new business models related with the collection, usage and production of knowledge. KIBS activities are based in the integration of external knowledge with the available knowledge from the client specific problem. From that, KIBS produce the codified knowledge corresponding to the specific need of the client firm Muller and Zenker (2001). This process is not unilateral: the knowledge obtained from interactions with clients is combined with the existing knowledge resulting in a learning process where both actors gain new knowledge (Muller and Zenker, 2001). As a result, KIS firms are important players in the development and transfer of knowledge.

Koch and Strotmann (2006) suggest that the production of KIS demands interaction and cooperation with customers and partners, where for young firms may be crucial, since they rely strongly to interactions, in order to promote learning processes and innovation for their development. Proximity to the client also have an important role on young firms. Since in knowledge-intensive services there is a significant part of knowledge and information connected to personal capabilities (tacit knowledge), the exchange and development of this knowledge requires proximity and trust. For these reasons, Koch and Strotmann (2006) suggests that spatial proximity have a positive effect on post-entry growth of KIBS firms. Moreover, localised knowledge spillovers may boost growth for young firms, since they depend heavily of external knowledge from other firms or universities (Audretsch et al., 2004). In fact, geographical proximity of universities may boost positive knowledge externalities, such as knowledge spillovers, since there is a higher inclination towards possible relationships and partnerships between universities and firms (Baptista and Mendonça, 2010).

The creation of knowledge and innovation is fuelled by profit incentives for which an intellectual property rights system is paramount. In the past, monopoly profits due to innovation were possible, however, due to the speed and short product cycles and information transfer, even with effective intellectual property right protection, monopolist profits are harder to achieve (Andersen, 2000). This led to a lack of formal barriers to entry allowing KIBS to react quickly to current demand. New firms are, however, sometimes unable to perform according to the high standards of the market, such as high problem solving competence, flexibility and adaptability, which can influence its survival (Strambach, 2001).

2.2.4 Portuguese Scenario

Portugal is a small country, with approximately 10 million habitants, mostly located in the North and coastline. It is characterised for having structural weaknesses that limit the competitive capacity of Portuguese companies such as low level of productivity, large number of small firms, low educational level and qualified workforce, along with low degree of innovation and competitiveness in certain markets. Between 2011 and 2015, Portugal entered in deep recession with severe repercussions to the economy and Portuguese households. The generated country's wealth decreased, investment fell, unemployment increased rapidly and, consequently, the risk of poverty and inequalities intensified within that period. With an average of 44 firms going to bankruptcy everyday, this scenario led to a massive wave of emigra-

tion, up to more than 350,000 people[1]. However, recent studies from OECD (2017) show that Portugal has been gradually recovering from this crisis, while undertaking structural reform programme since 2011 that covered a wide range of policy areas, product markets, labour markets, taxes, regulations and the public sector. These changes supported the recovery, leading to a successful rebalancing of the economy towards exports. In 2015, Portugal exported 40% of their GDP, more 13 percentage points than exports volume from 2005 (OECD, 2017).

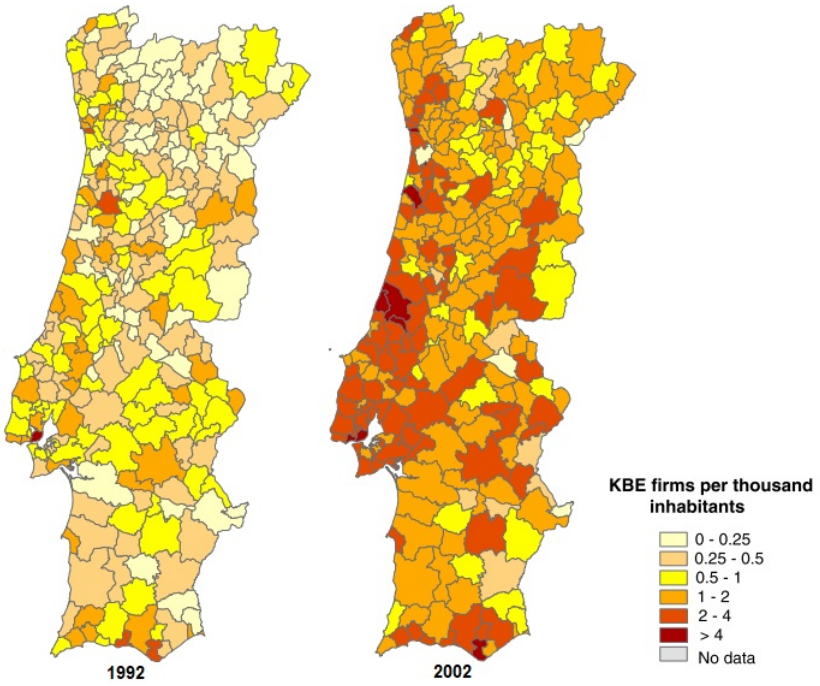


Figure 2.1: Distribution of knowledge-based firms in Portuguese municipalities in 1992 and 2002. Source: Baptista and Mendonça (2010).

Over the last years, the population employed in service sectors has rise significantly, representing over 70% current total employment in Portugal[2]. According to Baptista and Mendonça (2010), there was an increase on the number of Portuguese knowledge-based firms[3] in the period of 1992 to 2002, similarly to the general increase of firms related with knowledge in developed economies. Figure 2.1 shows that, in 1992, knowledge-based activities were mainly concentrated in the largest urban agglomerations, such as Lisbon, Oporto, Aveiro, Faro and surroundings, where in 2002 the geographical distribution became more even, while still having considerable differences between the coastline and inland areas. The degree of geographical concentration is mostly related with the local access to knowledge and human capital, where knowledge spillovers and proximity with clients have an important role the location of knowledge-based firms, since it promotes firm growth (Baptista and Mendonça, 2010; Koch and Strotmann, 2006; Audretsch et al., 2004). According to Carvalho and Pinto (2013), most customers for KIBS are located in the northern region, followed by Lisbon, Centre, Alentejo and Algarve where most services provided are R&D (44.7%); Management and other (32.4%); and Information and communication technologies (23%), which is aligned with the previous argument.

[1] Source: https://www.https://www.portugal.gov.pt/ficheiros-geral/programa-do-governo-pdf.aspx
[2] Source: https://www.pordata.pt/DB/Portugal/Ambiente+de+Consulta/Tabela
[3] It includes knowledge-based manufacturing and service firms.

To summarise, knowledge and innovation are gaining more importance in the economy, where KIS industry is acting as a B2B go-between for technology, innovation and economic progress, as problem-solving specialists on delivering knowledge input, allowing the creation of innovation (Miles, 2005). The research related to Portuguese knowledge-intensive services is still very recent, and those related with firm survival in knowledge-intensive industry are also scarce. With this study we intend to add some relevant insights of the Portuguese knowledge-intensive industry scenario to the literature.

Chapter 3

Data Characterisation

In this Chapter we present a detailed characterisation of our data-set provided by Statistics Portugal, with information regarding Portugal service firm's activity from year 2007 to 2015. By selecting the most relevant variables to evaluate firm's performance, according to firm survival determinants found in the literature, we describe the sample, and choose the variables to include in our further models.

3.1 Data-set and Scope

To perform this study, we use the Integrated Business Accounts System data-set (*Sistema de Contas Integradas das Empresas — SCIE*), provided by Statistics Portugal (*Instituto Nacional de Estatistica* — INE). The data-set comes from the integration process of anonymous statistical information of Portuguese firms, based on administrative data of the Simplified Business Information System (*Informação Empresarial Simplificada* — IES). This information also covers sole proprietary firms, through a protocol between INE and the Tributary and Customs Authority (*Autoridade Tributária e Aduaneira* — AT), complemented by data from the Statistic Units File (*Ficheiro de Unidades Estatísticas* — FUE), to provide a full coverage of statistical information and variables.

SCIE main focus is to characterise the firm's economic and financial behaviour, through a set of relevant variables for the business sector, along with ratios from its financial analysis. It also characterises the economic behaviour according to the geographical location, through the Portuguese Nomenclature of Territorial Units for Statistics (NUTS II) from Eurostat, at 2-digit code level: North (11); Algarve (15); Centre(16); Lisbon metropolitan area (17); Alentejo (18); Azores (20); and Madeira (30). The population of SCIE in each year n is composed by all firms (sole proprietaries, societies, and independent workers), excluding financial, insurances and non-market-oriented companies, that perform any goods and/or services activity during that period in Portugal.

Given the context of our study and information available, we classified service firms as knowledge-intensive services (KIS) or less knowledge-intensive services (LKIS) according to the CAE Rev.3, the Portuguese Classification of Activities (*Classificação Portuguesa de Actividades*), based on the Statistical Classification of Economic Activities in the European Community (NACE Rev.2) from Eurostat[4]. A

[4]Source: https://www.ine.pt/ine_novidades/semin/cae/CAE_REV_3.pdf

Table 3.1: Knowledge-intensity classification of services sectors.

Knowledge-intensive services	**CAE Code and Description**
Knowledge-intensive market services	50 Water transport. 51 Air transport. 69 Legal and accounting activities. 70 Activities of head offices; management consultancy activities. 71 Architectural and engineering activities; technical testing and analysis. 73 Advertising and market research. 74 Other professional, scientific and technical activities. 78 Employment activities. 80 Security and investigation activities.
High-tech knowledge-intensive services	59 Motion picture, video and television programme production, sound recording and music publishing activities. 60 Programming and broadcasting activities. 61 Telecommunications. 62 Computer programming, consultancy and related activities. 63 Information service activities. 72 Scientific research and development.
Knowledge-intensive financial services	64 Financial service activities. 65 Insurance, reinsurance and pension funding activities. 66 Activities auxiliary to financial services and insurance activities.
Other knowledge-intensive services	58 Publishing activities. 75 Veterinary activities. 84 Public administration and defence; compulsory social security. 85 Education. 86 Human health activities. 87 Residential care activities. 88 Social work activities without accommodation. 90 Creative, arts and entertainment activities. 91 Libraries, archives, museums and other cultural activities. 92 Gambling and betting activities. 93 Sports activities and amusement and recreation activities.
Less knowledge-intensive services	
Less knowledge-intensive market services	45 Wholesale and repair of motor vehicles and motorcycles. 46 Wholesale trade, except of motor vehicles and motorcycles 47 Retail trade, except of motor vehicles and motorcycles. 49 Land transport and transport via pipelines. 52 Warehousing and support activities for transportation. 55 Accommodation. 56 Food and beverage service activities. 68 Real estate activities. 77 Rental and leasing activities. 79 Travel agency, tour operator reservation service and related activities. 81 Services to buildings and landscape activities. 82 Office administrative, office support and other business support activities. 95 Repair of computers and personal and household goods.
Other less knowledge-intensive services	53 Postal and courier activities. 94 Activities of membership organisations. 96 Other personal service activities. 97 Activities of households as employers of domestic personnel. 98 Undifferentiated goods and services producing activities of private households for own use. 99 Activities of extraterritorial organisations and bodies.

Note: Classification according to CAE-Rev.3, based on NACE Rev.2.

sector is considered as knowledge-intensive if tertiary educated people employed represent more than 33% of the total employment in that activity. This definition is based on the average number of employed persons aged 15-64 years at aggregated EU-27 level in 2008 and 2009, according to the NACE Rev.2 in 2-digit, using the EU Labour Force Survey data[5]. Table 3.1 presents the detailed KIS and LKIS classification, available on 2-digit level (division level) and sub-divided into further groups, class and sub-classes, according to the social-economic statistical information and activity sector. KIS firms group is divided

[5]Source: https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an8.pdf

into high-tech knowledge-intensive services, knowledge-intensive market services, knowledge-intensive financial services and other knowledge-intensive firms. As for LKIS firms group, it is divided into less knowledge-intensive market services and other less knowledge-intensive services.

We restrict our analysis to the period from 2007 to 2015. Exceptionally, we include information regarding the year of entry for companies that enter the market after 2003 through a different data-set, to minimise estimation problems related with left-censoring. We chose to not include the remaining information from those years due to an adjustment occurred on the Portuguese classification of economic activities, namely, from CAE Rev.2.1 to CAE Rev.3, based on NACE Rev.2. This change could introduce some errors, leading to biased estimates. We do not have access to closures in the last observation (2015), and also to variables related to innovation and exports prior 2010. Furthermore, we exclude single-individual-owned firms from the sample, because this type of firms may have a different behaviour from the remaining firms, such as being non-profit oriented for example. We also exclude firms with no information regarding their sales, to avoid misleading conclusions to our analysis due to its lack of information.

3.2 Definitions of Variables

Our initial data-set contained over 300 variables for 1,438,003 observations, regarding the economic and financial activity of each firm. Due to our research main focus, we chose a subset of variables more adequate for the descriptive analysis, subsequent hypotheses and survival analysis models. According to several studies discussed on literature review, we characterise our sample according to the following variables: region, age, size, start-up size, innovation, exports, sales, growth rate and type of industry.

Dunne et al. (1988) suggest that exist similarities between the average of entries and closures among two-digit sectors and, for which, it gets stronger when examining market shares or relative sizes. Additionally, Fritsch et al. (2006) argue that regional economic environment has an influence on the success of new firms. Hence, for the definition of some variables, we use different thresholds by year, region and sector, to ensure a cohesive measure to capture the behaviour of different sectors in similar environment.

3.2.1 Age, Size and Start-up Size

The variable age covers the number of years in activity from the year of entry. Exceptionally, as mentioned before, we had access to information regarding the year of entry for firms created after 2003. This variable also covers multiple entries and exits. In order to simplify further analysis, we divide this variable into four categories: 1 to 2 years; 3 to 4 years; 5 to 6 years; and equal or more than 7 years.

To characterize firm size and start-up size, we resort to the information available, respectively, of the number of employees at the current year, and the number of employees at the year of firm's entry in the market. Due to the Portuguese market characteristics, where the great majority of firms are micro with 1 employee, and to facilitate further analysis with knowledge-intensity, we use the following simplified categorization of firm size and start-up size: 1 employee; 2 to 9 employees and equal or more than 10 employees.

3.2.2 Innovation, Exports and Growth Rate

Cefis and Marsili (2006) observed different patterns across sectors regarding innovation. That could happen because a sector or market is more receptive to innovative activities than others, or unfavourable economic conditions at the time, among other reasons. Thus, we consider that each firm within their environment, either external or internal, may have a distinct attitude and predisposition towards investment in innovation and, therefore, should also have a different threshold according to its location, market and year of comparison.

Hence, we proceed as follows to define innovators and non-innovators, based on innovation expenditure. Firstly, we consider that R&D and patents solely are not enough to measure the performance of services firms (Gotsch and Hipp, 2012). Thus, we add investment in intangible assets, tangible assets and employee training as innovation expenditure, since the scope of our study includes a large and heterogeneous set of service firms that may resort not only to R&D to develop new processes to their activities, but also to employee training among equipment as support to their services. Due to the large variety of firms, either by sales volume and/or size, we compute a ratio between the sum of these variables and sales of the current year, to analyse how much investment in innovation these firms were effectively making, according to their sales volume, as shown in Equation (3.1).

$$\begin{aligned} Innovation\ Ratio &= \frac{R\&D + Tangible\ and\ Intangible\ Assets\ Investment + Employee\ Training}{Total\ Sales} \\ &= \frac{Innovation\ Expenditure}{Total\ Sales} \end{aligned} \tag{3.1}$$

Afterwards, this ratio was compared with a threshold, defined by the average innovation ratio minus its standard deviation (s_d) by year, region and sector. Firms with a value superior to this threshold are considered innovators, and those with a value under this threshold were considered non-innovators[6]. Therefore, the variable innovator is a dummy variable where it is 1 if the firm is considered innovator and 0 if the firm is non-innovator.

We followed a similar approach to identify exporting firms: we compare the ratio between the sum of all sales from overseas and the total sales (Equation (3.2)), with a threshold that is the average of the ratio minus its standard deviation by year, region and sector. Those firms with a value higher than this threshold were considered exporters, and those below were considered non-exporters[6].

$$Export\ Ratio = \frac{InternationalSales}{Total\ Sales} \tag{3.2}$$

The reason for this comparison is similar to the one from variable innovation, since firms within the same industry and region may have different conditions, markets and predispositions to export. For example, a firm located near the border between Portugal and Spain may export more than a firm located in Lisbon, all else equal. Thus, the variable exporter is also a dummy variable which is 1 if the firm is an exporter and 0 if it is a non-exporter.

To compute growth rate, we considered the sales per employee as a good reference to comprise the evolution of the firm's efficiency and productivity, per person employed, as shown in Equation (3.3).

$$GrowthRate_i = \frac{SalesPerEmployee_i - SalesPerEmployee_{i-1}}{SalesPerEmployee_{i-1}},\ i = 1, \ldots, n \tag{3.3}$$

[6]The validity of this comparison resorting to the average ratio was tested and confirmed in the Kaplan-Meier estimates analysis.

Here, we define that a firm is growing if the growth rate is positive, in terms of sales per employee. Otherwise, if the growth rate is negative or null, then the firm is not growing. Table 3.2 summarizes the definition of innovator, exporter and growing firm.

Table 3.2: Definition of innovators, exporters and growing firms.

Classification	Definition
Innovator	$InnovationRatio_{ij} > \overline{InnovationRatio}_i - s_d$
Non-innovator	$InnovationRatio_{ij} \leq \overline{InnovationRatio}_i - s_d$
Exporter	$ExportRatio_{ij} > \overline{ExportRatio}_i - s_d$
Non-exporter	$ExportRatio_{ij} \leq \overline{ExportRatio}_i - s_d$
Growing	$GrowthRate_{ij} > 0$
Not growing	$GrowthRate_{ij} \leq 0$

Note: ratios calculated by year, region and sector.

3.3 Descriptive Analysis

This Section shows the main characteristics of our sample, according to the variables described above in Section 3.2. Additionally, we also provide some insight regarding firm's performance, such as sales and sales per employee. Table 3.3 summarises the definition of the variables used throughout this dissertation.

Table 3.3: Summary of variables' description.

Variable	Description
KIS	Dummy variable, 1 if the firm is KIS, 0 otherwise (LKIS).
Age	Number of years that the company is active.
Size	Current number of employees.
Start-up size	Number of employees in the first year of activity.
Growth rate	Sales per employee annual growth rate.
Growing	Dummy variable, 1 if the firm is growing, 0 if the firm is not growing.
Innovation expenditure	Sum of R&D, employee training, tangible and intangible assets investment.
Innovation ratio	Ratio between innovation expenditure and total sales.
Innovator	Dummy variable, 1 if the firm is an innovator, 0 otherwise.
Total exports	International sales.
Export ratio	Ratio between international sales and total sales.
Exporter	Dummy variable, 1 if the firm is an exporter, 0 otherwise.

As a result from the restrictions mentioned in Section 3.1, our final sample is composed by 851,148 observations, corresponding to 223,452 firms. Our sample account with 69,604 (30%) KIS firms and 154,592 (70%) LKIS firms. We should note that the number of observations may vary when including certain variables. For instance, we do not have access to the information related to start-up size from all firms. Also, as mentioned before, we only have information regarding some components of the variables related to export and innovation after 2009.

3.3.1 Entries and Exits

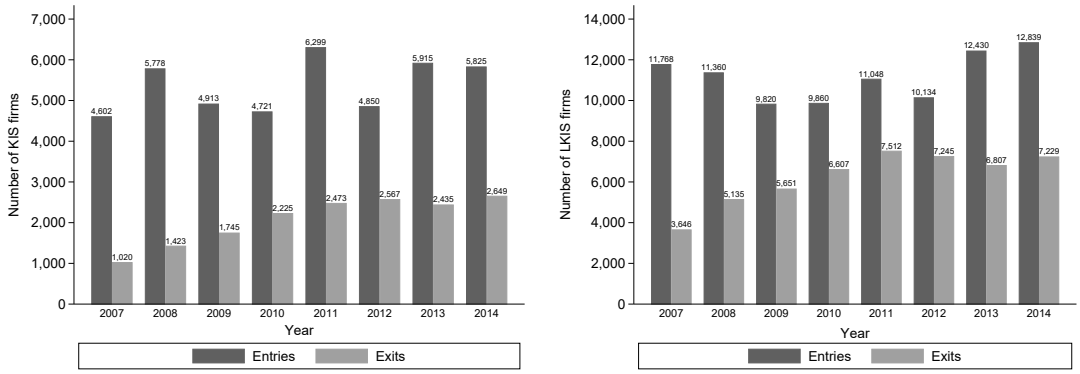
Table 3.4 shows the proportion of KIS and LKIS firms over the years. We may notice a general increase of the total number of firms, with a small deceleration in 2011 due to the economic recession.

Moreover, there was an overall trend of a decreasing share of LKIS firms and increasing share of KIS firms in the market. This detail may be a sign of the growing expansion of the KIS market.

Table 3.4: Number of KIS and LKIS firms by year.

Year	Number of firms					
	LKIS		KIS		Total	
	No.	%	No.	%	No.	%
2007	45,264	71.9	17,698	28.1	62,962	100.0
2008	51,695	70.1	22,054	29.9	73,749	100.0
2009	55,403	68.9	25,013	31.1	80,416	100.0
2010	58,623	68.1	27,435	31.9	86,058	100.0
2011	62,231	66.8	30,983	33.2	93,214	100.0
2012	63,808	66.1	32,758	33.9	96,566	100.0
2013	68,365	65.8	35,608	34.2	103,973	100.0
2014	73,991	65.7	38,548	34.3	112,539	100.0
2015	93,976	66.3	47,695	33.7	141,671	100.0
Total	573,356	67.4	277,792	32.6	851,148	100.0

Figure 3.1 reveals the number of entries and exits by knowledge-intensity. Considering the number of entries and exits in both type of firms, we may observe a general deceleration of entries and a steady increase of closures on both type of firms, due to the worldwide economic recession at 2008 and the following Portuguese economic crisis in 2011. Then, there is a slight recovery in the subsequent years, where the number of closures and entries stabilise. Thus, we may conclude that the economic and financial instability between 2008 and 2013 had a negative effect on entries, while having a positive effect on exits.



(a) KIS **(b)** LKIS

Figure 3.1: Entries and exits of firms by knowledge-intensity and year.

More specifically, the decrease on entries reveals some caution on behalf of some entrepreneurs from entering the market under these conditions (and tighter financial constraints), while the increase of closures unveils the expected vulnerability of services firms to unfavourable external environments. In general, we may also notice a higher proportion of entries/exits from KIS sector. This could be related to lower set up costs and barriers to entry in KIS markets, and that higher skilled/educated workforce may identify and exploit opportunities for new business creation in KIS sector (Baptista and Mendonça, 2010). Also, in both knowledge-intensity categories, we see an abnormal increase of entries

in 2011. This may be related to the fact that, when facing unemployment prospects, individuals may resort to self-employment by starting a business on their own (Headd, 2003), often called necessity entrepreneurship. Moreover, founders with higher education tend to be innovators and have higher odds of obtaining external financing to open a business (Baptista et al., 2012). We may reinforce these claims through a detailed look of the year of 2011[7], where most entries are from firms with 1 employee, and LKIS firms had a higher decay on firms leaving the market than KIS firms. Therefore, we could say from this preliminary look that, in this particular year, the difference between KIS and LKIS entries and exits may lie on the positive impact that education level has on firm survival and entrepreneurship (Baptista et al., 2012).

3.3.2 Sales, Sales per Employee and Growth Rate

Table 3.5 shows the sales, sales per employee and average growth rate across the years of 2007 to 2015. The figures reveal that total sales and sales per employee have increased over the years, perhaps consequence of the general increase of firms in the market. We also observe a stagnation on the total sales and sales per employee in 2011 and 2012, probably due to the Portuguese economic recession. This is more evident while examining the evolution on the average growth rate, where it starts to decelerate from 2010 to 2014, a period of economic retrenchment. This deceleration was more accentuated among LKIS firms, probably because these firms are more vulnerable and less resilience to adverse macroeconomic conditions.

Table 3.5: Sales, sales per employee and average growth rate by year.

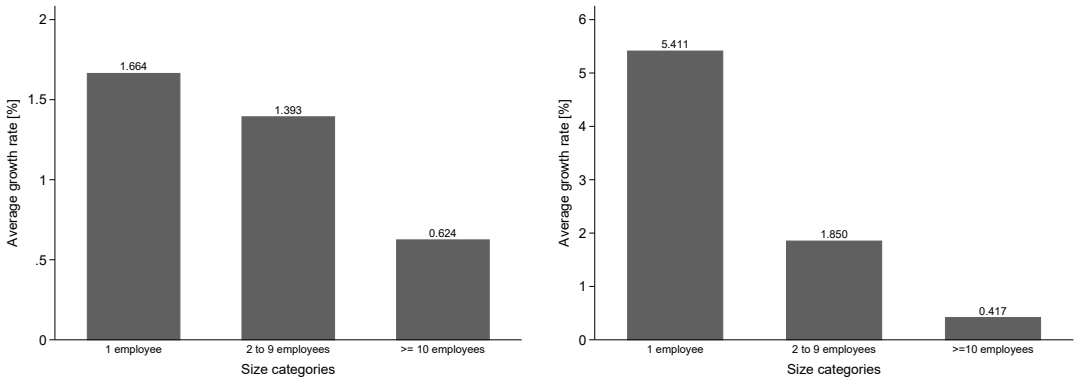
Year	Sales $[10^9€]$		Sales per employee $[10^9€]$		Average growth rate [%]	
	KIS	LKIS	KIS	LKIS	KIS	LKIS
2007	3.09	13.60	1.04	4.06	-	-
2008	4.23	16.50	1.16	4.68	1.86	3.59
2009	4.95	17.70	1.37	4.92	1.73	4.46
2010	5.42	20.80	1.55	5.58	1.13	2.63
2011	5.68	21.80	1.62	5.69	1.12	1.39
2012	5.65	21.80	1.66	5.75	1.01	1.65
2013	6.19	23.30	1.78	6.21	1.38	1.71
2014	6.84	26.10	2.00	6.81	1.11	4.86
2015	9.43	36.20	2.55	9.39	2.45	3.97

Figure 3.2 presents the average growth rate by size category and knowledge-intensity. We can see that firms with 1 employee have a higher growth rate mean among the remaining categories. The gap is more clear for LKIS firms that also have higher growth rates means than KIS firms. This result suggests the opposite of the old claim from Gibrat (1931), where it says that growth and size were not related. Instead, it is aligned with findings from Evans (1987b) and Mansfield (1962), where their studies suggest higher growth rates for smaller firms than larger firms, i.e., firm growth decreases with firm size.

3.3.3 Region

Table 3.6 and 3.7 comprises the proportion of firms by region, knowledge-intensity and year, according to the information available in the data-set. As mentioned in Chapter 2, the Portuguese economy is

[7] see Figure A.1 in Appendix A.



(a) KIS **(b)** LKIS

Figure 3.2: Average growth rate by knowledge-intensity and size category (whole sample).

mostly composed by micro companies, where the majority are located in the Lisbon urban area and the North region. In Table 3.6 and 3.7, we may observe the same pattern in our sample where, generally, Portuguese service firms are mostly located in Lisbon and North region of the country. This may be justified by the population density, which is higher along the Portuguese coastline and North area. Also, according to Baptista and Mendonça (2010), local access to knowledge and human capital lures the entry of knowledge-based firms into regions.

Table 3.6: Proportion of KIS firms by region and year [%].

	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
North	28.6	28.8	28.5	29.2	29.6	29.5	30.0	30.0	30.1	29.5
Algarve	4.1	4.1	4.2	4.0	3.8	3.8	3.7	3.7	3.8	3.9
Centre	16.3	16.0	16.3	16.5	16.0	16.0	15.8	15.6	15.8	16.0
Lisbon	43.2	43.4	43.3	42.7	43.3	43.5	43.5	43.7	43.0	43.3
Alentejo	4.3	4.4	4.5	4.6	4.5	4.3	4.2	4.2	4.3	4.4
Azores	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.3	1.2
Madeira	2.3	2.1	2.0	1.8	1.7	1.6	1.6	1.6	1.7	1.8
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

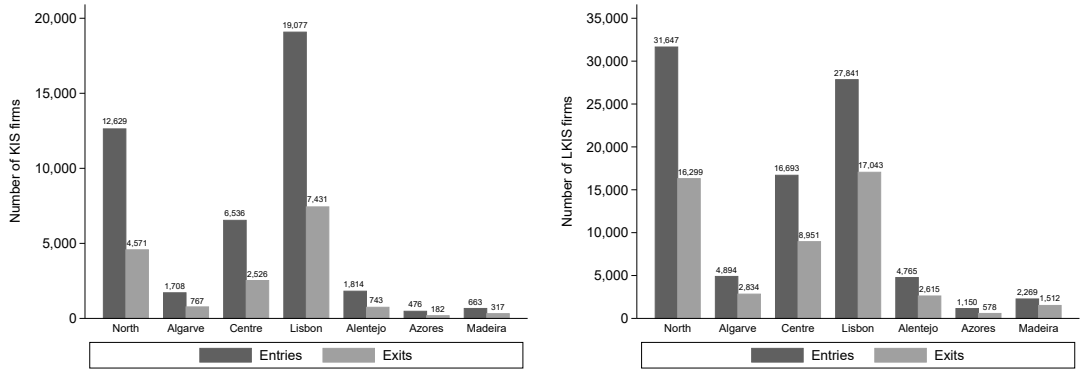
According to Table 3.6, approximately 43% of KIS firms are located in Lisbon metropolitan area, 29% in North, 16% in Centre, and 12% are distributed to the remaining areas, where Azores area account with the lowest percentage with 1.2% of KIS firms. As for the LKIS firms, the data in Table 3.7 shows

Table 3.7: Proportion of LKIS firms by region and year [%].

	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
North	32.6	33.0	33.5	34.1	34.8	35.4	35.9	35.9	35.4	34.7
Algarve	5.5	5.6	5.6	5.5	5.3	5.2	5.2	5.3	5.5	5.4
Centre	19.6	19.6	19.5	19.7	19.8	19.7	19.6	19.4	19.2	19.6
Lisbon	32.0	31.7	31.1	30.6	30.2	29.9	29.6	29.8	30.3	30.5
Alentejo	5.6	5.7	5.8	5.7	5.7	5.6	5.5	5.5	5.5	5.6
Azores	1.4	1.5	1.5	1.5	1.4	1.5	1.5	1.4	1.5	1.5
Madeira	3.1	3.1	3.0	2.9	2.8	2.7	2.6	2.6	2.5	2.8
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

that the distribution of firms is slightly different than KIS firms, where North area has the highest share of LKIS firms, with approximately 35%, followed by Lisbon area with 31%, and Centre area with 19.6%.

The remaining firms are distributed into the other areas where Azores has the lowest percentage, with 1.4%. Here, we notice a small growing pattern of the proportion of LKIS firms in the northern area and decrease of the percentage firms in Lisbon area, until 2013. This was probably caused by the higher vulnerability of LKIS in urban areas, possibly triggered by the increased competitiveness in those areas and the economic crisis. We may also observe a higher proportion of KIS firms in urban areas as oppose to LKIS firms. In fact, there are several studies suggesting that KIBS sectors tend to be more concentrated in large cities due to several reasons, namely: interactivity, since proximity promotes the development of better relationships with their clients; and sensitivity of the market or quality, due to the proximity of knowledge sources and promoters, such as universities; and type of knowledge (Wood, 2003; Baptista and Mendonça, 2010).



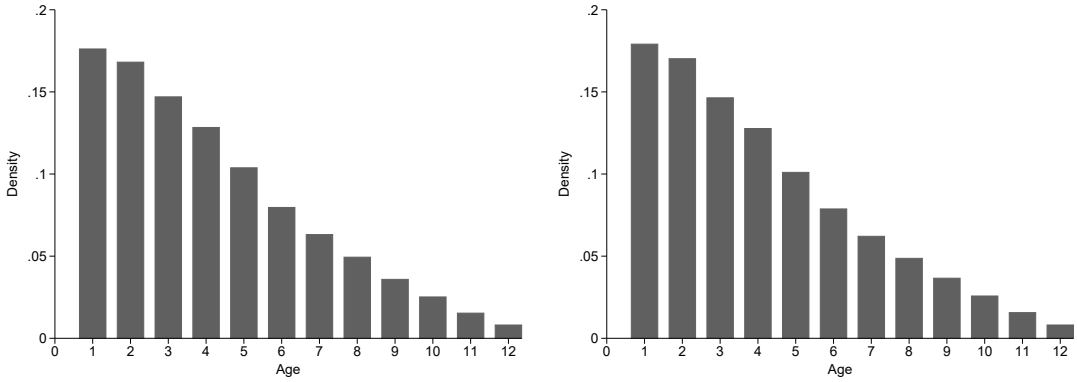
(a) KIS **(b)** LKIS

Figure 3.3: Entries and exits of firms by knowledge-intensity and region (whole sample).

We also characterise the dynamic of entries and exits of our sample according to their location, displayed in Figure 3.3. Among KIS firms, the highest share of entries and exits occurred in Lisbon area, followed by the North region, being the most populated and competitive areas for this type of firms. As for the LKIS firms, aligned with the conclusions from Table 3.7, the North region is the one with most entries, followed by Lisbon area. This detail can be probably explained by the fact that Lisbon area is more competitive due to higher concentration of firms in that area. Stearns et al. (1995) study reinforces this argument, where it states that new firms have higher probability of leaving the market in urban areas due to the competitive density. Their study also suggests that rural locations allows firms to exploit a niche with limited competition, which may explain the dynamic of entries and exits in the North region. Another possible explanation lies on the fact that the North region includes the metropolitan urban area of Oporto, where there is high population density and, consequently, a high share of firms as well.

3.3.4 Age

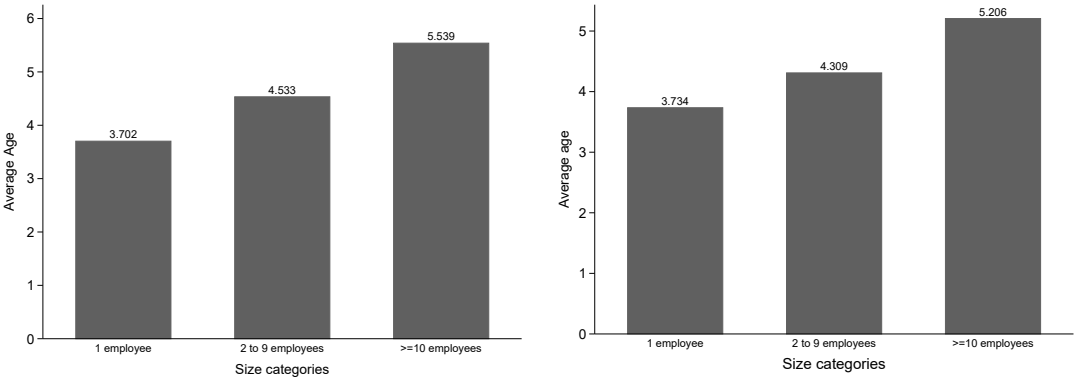
Figure 3.4 shows the firm distribution, according to their age. It is right-skewed, which indicates that most observations of our sample correspond to firms with at least 2 years, where the average age is approximately 4 years. This result is in agreement with findings discussed in Chapter 2, stating that young firms are the major responsible of firm dynamics and are more susceptible to closure (Dunne and Hughes, 1994; Evans, 1987a; Wagner, 1994; Mata and Portugal, 1999).



(a) KIS **(b)** LKIS

Figure 3.4: Distribution of firms by knowledge-intensity and age (whole sample).

Figure 3.5 shows the average firm age according to size categories. We may say that in our sample, in average, the majority of large firms survives longer than small firms. It also shows that KIS and LKIS firms have approximately the same average age within the category of firms with 1 employee and, in the remaining categories, KIS firms have a higher average age than LKIS firms. This result may suggest a positive correlation between size and duration, aligned with previous research (Dunne and Hughes, 1994; Evans, 1987a). Additionally, it give us clues regarding possible interactions between type of industry, duration and size, where LKIS firms with more than 10 employees have a lower average age than KIS firms within the same category of size. Same pattern happens in firms with 2 to 9 employees.



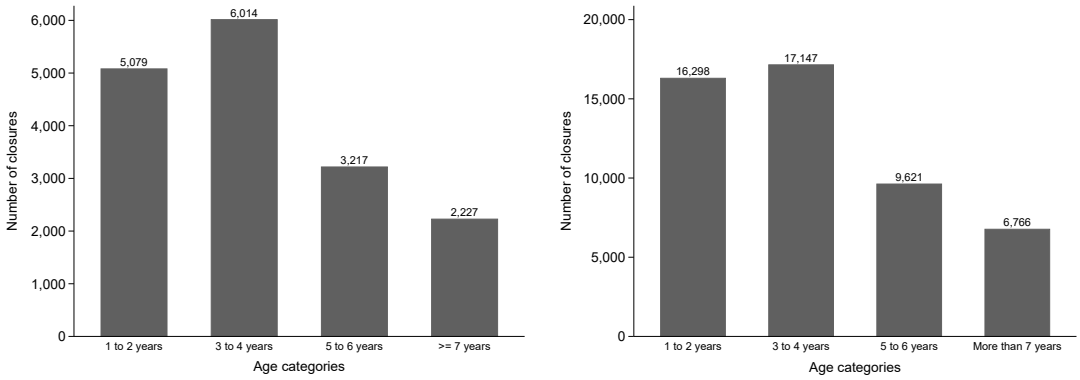
(a) KIS **(b)** LKIS

Figure 3.5: Average firm age by knowledge-intensity and size category (whole sample).

Figure 3.6 shows the number of closures occurred by age category. We may observe that a high share of KIS firms leave the market at the age of 3 to 4 years, whereas for LKIS firms it is also more frequent to leave the market at that age category but also at younger age, with 1 to 2 years of activity. These results are in line to those obtained in Figure 3.5. Additionally, this may be another sign of the higher vulnerability that LKIS firms have at early age to exit the market.

3.3.5 Size and Start-up Size

Since size and start-up size are important determinants of firm survival, as discussed in Chapter 2, we characterise our sample accordingly to these two variables. As shown in Section 3.2, size and start-



(a) KIS **(b)** LKIS

Figure 3.6: Number of closures by knowledge-intensity and age category (whole sample).

up size was computed through the number of employees of the respective year and from the first year of activity. Moreover, we also display these variables categorically, according to the Portuguese service market structure. Most firms in our sample are micro firms, i.e., firms composed by 1 to 10 employees, which is a common feature of the Portuguese market. Table 3.8 and 3.9 present the characterisation of our sample according to size categories and knowledge-intensity.

Table 3.8: Number of KIS firms by size category and year.

Year	Number of employees							
	1 employee		2 to 9 employees		$\geq$ 10 employees		Total	
	No.	%	No.	%	No.	%	No.	%
2007	9,003	50.9	7,988	45.1	707	4.0	17,698	100.0
2008	11,164	50.6	9,960	45.2	930	4.2	22,054	100.0
2009	12,762	51.0	11,145	44.6	1,106	4.4	25,013	100.0
2010	13,824	50.4	12,365	45.1	1,246	4.5	27,435	100.0
2011	16,209	52.3	13,454	43.4	1,320	4.3	30,983	100.0
2012	17,557	53.6	13,877	42.4	1,324	4.0	32,758	100.0
2013	19,316	54.2	14,873	41.8	1,419	4.0	35,608	100.0
2014	20,669	53.6	16,312	42.3	1,567	4.1	38,548	100.0
2015	25,165	52.8	20,212	42.4	2,318	4.9	47,695	100.0
Total	145,669	52.4	120,186	43.3	11,937	4.3	277,792	100.0

As shown in Table 3.8, most KIS firms have 1 employee, corresponding to approximately more than half of the total number of KIS each year, followed by firms with 2 to 9 employees with a slightly smaller share. KIS firms with more than 10 employees account with the lowest share, varying between 4 and 5%. We may see a small increase of the proportion of firms with 1 employee over the years until 2013, whereas the percentage of firms with 2 to employees decreased in the same period. The trend turned after 2013. Maybe it is related with the phenomenon that is explained in Section 3.3.1, where self-employment tend to increase in periods of crisis and economical retrenchment.

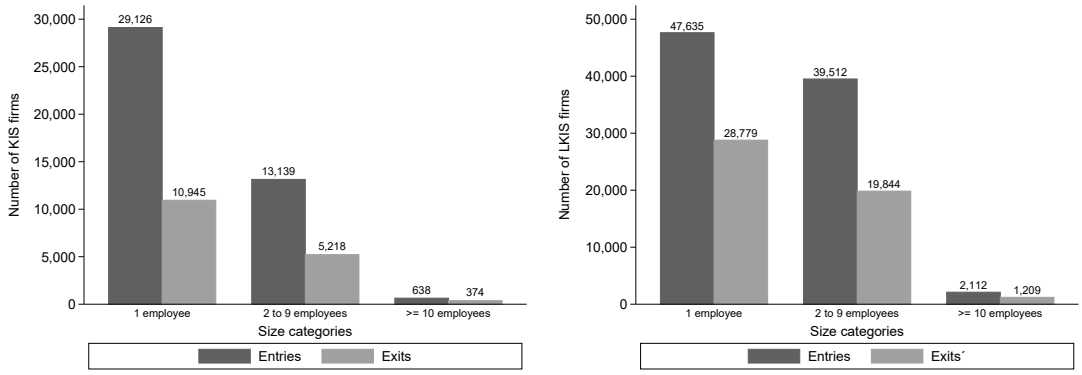
In Table 3.9, as opposed to what was observed for KIS firms, firms with 2 to 9 employees are more frequent among LKIS firms, followed by firms with 1 employee, where less than 2% are firms with more than 10 employees. At first sight, we may conclude that LKIS firms tend to be larger than KIS firms. This is aligned with studies of knowledge-based firms, suggesting that LKIS firms tend to benefit more

of economies of scale than KIS and, therefore, usually operate in larger scale (Tether and Hipp, 2002).

Table 3.9: Number of LKIS firms by size category and year.

Year	Number of employees							
	1 employee		2 to 9 employees		$\geq$ 10 employees		Total	
	No.	%	No.	%	No.	%	No.	%
2007	18,042	39.9	25,059	55.4	2,163	4.8	45,264	100.0
2008	20,041	38.8	28,945	56.0	2,709	5.2	51,695	100.0
2009	21,578	38.9	30,810	55.6	3,015	5.4	55,403	100.0
2010	22,386	38.2	32,846	56.0	3,391	5.8	58,623	100.0
2011	24,219	38.9	34,441	55.3	3,571	5.7	62,231	100.0
2012	25,878	40.6	34,376	53.9	3,554	5.6	63,808	100.0
2013	28,488	41.7	36,157	52.9	3,720	5.4	68,365	100.0
2014	30,562	41.3	39,296	53.1	4,133	5.6	73,991	100.0
2015	40,335	42.9	47,830	50.9	5,811	6.2	93,976	100.0
Total	231,529	40.4	309,760	54.0	32,067	5.6	573,356	100.0

Figure 3.7 unveils the number of entries and exits by size category. The majority of KIS firms enter the market with 1 employee, whereas LKIS firms often enter with 1 to 9 employees evenly, but with higher number of entries. These results are aligned with those observed in Table 3.8 and 3.9. A possible explanation for this difference could be the fact that KIS firms have less sunk costs at entry and involve activities more knowledge-intensive instead of labour intensive, i.e., it is more important and valuable to hire qualified and experienced workforce, even if it is in smaller quantity, than hire an extensive number of employees, which is more common in LKIS firms. Therefore, it is less beneficial for KIS firms to enter the market in larger scale than LKIS firms (Tether and Hipp, 2002).



(a) KIS **(b)** LKIS

Figure 3.7: Entries and exits of firms by knowledge-intensity and size category (whole sample).

Another important determinant of firm survival is the number of employees in the first year of activity (start-up size). We characterise this variable for a total of 49,222 observations, since we only had information related to the firm start-up size from companies that enter the market within the period of our observations, i.e., from 2007 and 2015. Table 3.10 and 3.11 reveals the number of firms by start-up size category and knowledge-intensity.

In general, we may notice that service firms start their activity in small scale, with 1 to 9 employees. Among KIS firms this is more evident, where firms with 1 employee represent 60 to 70% of the total number of KIS firms, whereas firms with 2 to 9 employees represent 37 to 27%. The remaining share of firms

Table 3.10: Number of KIS firms by start-up size category and year.

Year	Number of employees at first year of activity							
	1 employee		2 to 9 employees		$\geq$ 10 employees		Total	
	No.	%	No.	%	No.	%	No.	%
2007	2,850	61.3	1,714	36.9	85	1.8	4,649	100.0
2008	3,694	63.6	1,991	34.3	119	2.1	5,804	100.0
2009	3,249	66.0	1,594	32.4	82	1.7	4,925	100.0
2010	3,129	66.1	1,538	32.5	64	1.4	4,731	100.0
2011	4,538	71.7	1,727	27.3	60	0.9	6,325	100.0
2012	3,462	70.9	1,355	27.8	63	1.3	4,880	100.0
2013	4,241	71.4	1,614	27.2	84	1.4	5,939	100.0
2014	4,117	69.8	1,692	28.7	88	1.5	5,897	100.0
2015	4,310	71.0	1,657	27.3	105	1.7	6,072	100.0
Total	33,590	68.2	14,882	30.2	750	1.5	49,222	100.0

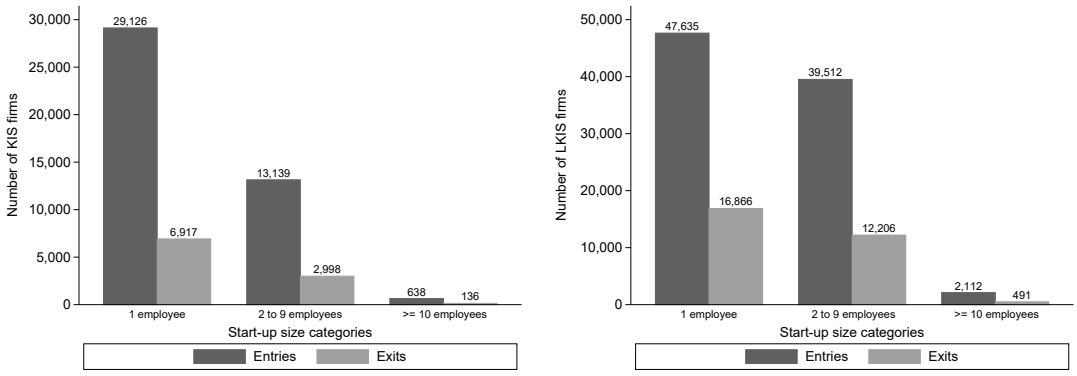
with more than 10 employees may vary between 0.9 and 2.1%. We observe a declining share of entries among firms with more than 10 employees, whereas the entry of firms with 1 employee increased from 2009 to 2011. Once more, this may be related with the economic recession and necessity employment rise in that period. Plus, it seems riskier to enter the market with a large number of employees under such unfavourable economic conditions.

Table 3.11: Number of LKIS firms by start-up size category and year.

Year	Number of employees at first year of activity							
	1 employee		2 to 9 employees		$\geq$ 10 employees		Total	
	No.	%	No.	%	No.	%	No.	%
2007	5,806	48.7	5,836	48.9	283	2.4	11,925	100.0
2008	5,720	50.1	5,395	47.3	296	2.6	11,411	100.0
2009	5,131	52.0	4,456	45.1	285	2.9	9,872	100.0
2010	5,086	51.4	4,571	46.2	240	2.4	9,897	100.0
2011	6,102	54.9	4,749	42.8	254	2.3	11,105	100.0
2012	5,799	56.9	4,135	40.6	256	2.5	10,190	100.0
2013	6,991	56.0	5,253	42.0	249	2.0	12,493	100.0
2014	7,361	56.6	5,392	41.4	263	2.0	13,016	100.0
2015	7,877	58.3	5,344	39.6	284	2.1	13,505	100.0
Total	55,873	54.0	45,131	43.6	2,410	2.3	103,414	100.0

As for LKIS firms, the proportion of firms is more even, where the share of firms with 1 employee vary between 48.7 and 58.7%, followed by firms with 2 to 9 employees between 39.6 to 48.6%. Somewhat different to KIS, firms with more than 10 employees have more presence with 2 to 3%. Here, we also observe a reduction of the share of firms with 2 to 9 employees and firms with more than 10 employees between 2010 and 2013, probably because it was riskier to enter the market in that period with a large number of employees.

Figure 3.8 presents the dynamic of entries and exits by start-up size category. Similarly to the scenario observed in Figure 3.7, it is more common for KIS firms to enter the market with 1 employee. As for LKIS firms, they also enter to the market at a smaller scale but with a lightly higher number of employees (1 to 10). This similar pattern occurs because it is more valuable for LKIS firms to have a larger workforce due to their labour intensive activities.



(a) KIS **(b)** LKIS

Figure 3.8: Entries and exits of firms by knowledge-intensity and start-up size category (whole sample).

3.3.6 Innovation

To describe our sample considering the variable innovation, we consider the period between 2010 and 2015, since we do not have information available about the components of this variable prior 2009. Table 3.12 reveals the total innovation expenditure and innovation ratio average, over the years. For KIS firms, the innovation expenditure starts to decrease in 2011 until 2013 and, after that period, it increases at a slow pace. Same pattern occurs with the average innovation ratio. The overall innovation expenditure and the respective ratio average decreases from 2010 to 2013 for LKIS firms. Once again, this pattern was triggered by a clear contraction and precaution from firms, due to the economic instability felt during those years.

Table 3.12: Innovation expenditure and average innovation ratio by knowledge-intensity and year.

Year	Innovation expenditure [10^9€]		Average inovation ratio [%]	
	KIS	LKIS	KIS	LKIS
2010	0.79	1.34	82.55	77.60
2011	0.68	1.07	44.56	41.93
2012	0.49	0.85	43.19	46.00
2013	0.58	0.96	50.82	38.87
2014	0.54	1.29	35.07	68.57
2015	1.18	2.68	85.48	122.56

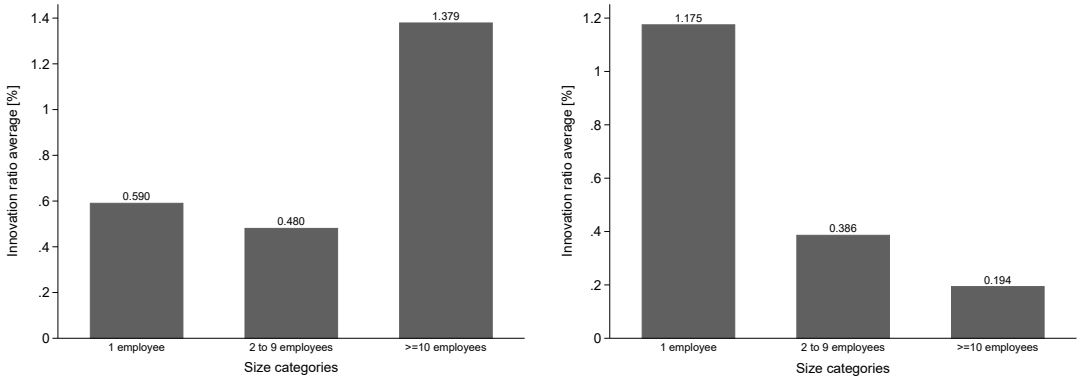
Table 3.13 shows the number of innovators and non-innovators by knowledge-intensity, according to the definition described in Section 3.2.2. In the first year of observations, we notice a higher percentage of innovators than non-innovators for both type of knowledge-intensity. However, over the years, the share of non-innovators starts to grow. This may be related to the reduction of innovation expenditure in the recession period. It becomes unsafe to invest in innovation where the general market is not as receptive as in periods of expansion. Plus, since most KIS firms are focused in B2B markets (KIBS), this caution from firms may amplify the reduction of the innovation expenditure over those years. Also, our definition of innovators and non-innovators is based in a comparison with an average value and, since supposedly non-innovators will eventually leave the market, the arithmetic mean will naturally rise and virtually reduce the number of innovators in the sample. Yet, this problem is mitigated by the entrance

of new and innovators firms in the market, lowering the average innovation ratio and rebalancing this threshold.

Table 3.13: Number of innovators and non-innovators firms by knowledge-intensity and year.

Year	KIS						LKIS					
	Non-Innovator		Innovator		Total		Non-Innovator		Innovator		Total	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
2010	10,407	37.9	17,028	62.1	27,435	100.0	24,282	41.4	34,341	58.6	58,623	100.0
2011	14,351	46.3	16,632	53.7	30,983	100.0	31,246	50.2	30,985	49.8	62,231	100.0
2012	16,742	51.1	16,016	48.9	32,758	100.0	34,173	53.6	29,635	46.4	63,808	100.0
2013	17,988	50.5	17,620	49.5	35,608	100.0	35,287	51.6	33,078	48.4	68,365	100.0
2014	19,750	51.2	18,798	48.8	38,548	100.0	38,953	52.6	35,038	47.4	73,991	100.0
2015	25,120	52.7	22,575	47.3	47,695	100.0	50,452	53.7	43,524	46.3	93,976	100.0
Total	104,358	49.0	108,669	51.0	213,027	100.0	214,393	50.9	206,601	49.1	420,994	100.0

Figure 3.9 shows the average innovation ratio by size categories for KIS and LKIS firms. It seems that KIS larger firms ($\geq$ 10 employees) have the highest innovation ratio average, followed by LKIS small firms with 1 employee. These two results may seem counter-intuitive, since innovation is riskier for small firms due to the unstable return from investing (Coad et al., 2016). Withal, since small firms are more susceptible to perish, they benefit the most from innovation to increase their chances of survival and tend to invest more (Cefis and Marsili, 2006; Cooley and Quadrini, 2001). Regarding the high innovation ratio mean from KIS large firms, this result seems unusual. Large firms are usually more stable in terms of growth, with a better understanding of their cost structures and efficiency levels and, consequently, with stable profit outcomes, thus, are less compelled into innovative activities (Dunne et al., 1988; Jovanovic, 1982). However, since we are dealing with KIS firms and they are usually small, perhaps large KIS firms need more investments in innovation due to the nature of their particular activities. Also, large firms are less financially constrained (Beck and Demirguc-Kunt, 2006), thus, KIS large firms may be more compelled to invest in innovation regularly.

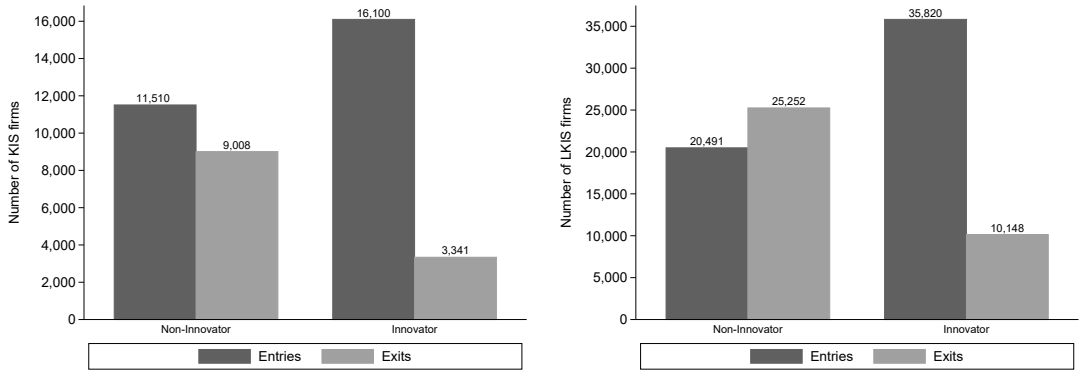


(a) KIS **(b)** LKIS

Figure 3.9: Average innovation ratio by knowledge-intensity and size category (whole sample).

Figure 3.10 presents the entries and exits over the classification of innovators and non-innovators. As we can see, a high proportion of KIS and LKIS firms enters the market as innovators. For KIS firms, is well known and studied their role of introducing innovation to the market (Muller and Zenker, 2001; Miles et al., 1995). As for LKIS firms, this trait is not often referenced in the literature, however, we

may speculate that this type of firms may need initial investment in the beginning of their activity to outstand themselves from the competition. Also, we observe that there is greater amount of closures for non-innovators firms, which may indicate a higher vulnerability for non-innovators LKIS firms to exit the market.



(a) KIS **(b)** LKIS

Figure 3.10: Entries and exits of firms by knowledge-intensity and innovation category (whole sample).

3.3.7 Exports

In this Section we present a description of exports from 2010 to 2015, since there is no information available from their components prior 2010. Table 3.14 presents the total exports and export ratio average, over the years. The figures show a gradual increase in exports over the years. Same thing occurs for the export ratio average from KIS firms. For LKIS firms, the ratio also increases slowly, with a fallback in 2012. An explanation for that lies on the conclusions discussed in Chapter 2, where exports can be a source of improved productivity and an escape from an eventual economic crisis (Bernard et al., 1995; Hirsch and Lev, 1971; Wagner, 1995).

Table 3.14: Total exports and average export ratio by knowledge-intensity and year.

Year	Total exports [10^9€]		Average export ratio [%]	
	KIS	LKIS	KIS	LKIS
2010	0.59	2.38	3.94	4.28
2011	0.76	2.72	4.99	5.02
2012	0.83	3.08	5.05	4.88
2013	1.01	3.36	5.58	5.01
2014	1.09	3.51	6.01	5.05
2015	1.64	5.57	6.90	5.47

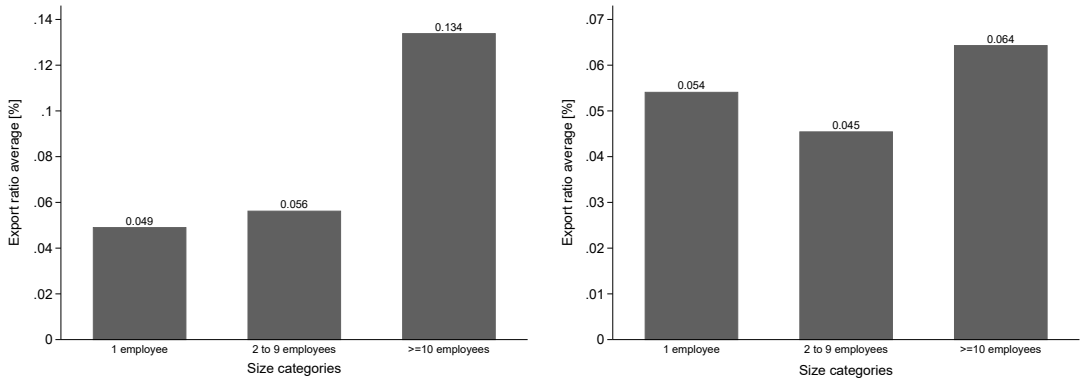
Table 3.15 shows the number of exporters and non-exporters firms by knowledge-intensity. From these results, we may say that the percentage of exporters either for KIS and LKIS firms is similar and low, from 10% to 15%. For both type of firms, there was a gradual increase of the share of exporters over the years. Here, the explanation may be identical to the one related with the classification on innovators and non-innovators, where the comparison to export ratio mean have an influence on this trend. Another explanation may lie in the fact that firms tend to look for alternative markets when facing an economic recession, and one possible solution is to export abroad. Also, ICT tools have improved greatly over the

years, facilitating the ability for some service firms to export their services.

Table 3.15: Number of exporters and non-exporters firms by knowledge-intensity and year.

Year	KIS						LKIS					
	Non-Exporter		Exporter		Total		Non-Exporter		Exporter		Total	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
2010	24,624	89.8	2,811	10.2	27,435	100.0	51,949	88.6	6,674	11.4	58,623	100.0
2011	27,359	88.3	3,624	11.7	30,983	100.0	54,271	87.2	7,960	12.8	62,231	100.0
2012	28,682	87.6	4,076	12.4	32,758	100.0	55,436	86.9	8,372	13.1	63,808	100.0
2013	30,797	86.5	4,811	13.5	35,608	100.0	58,952	86.2	9,413	13.8	68,365	100.0
2014	32,977	85.5	5,571	14.5	38,548	100.0	63,530	85.9	10,461	14.1	73,991	100.0
2015	40,371	84.6	7,324	15.4	47,695	100.0	80,435	85.6	13,541	14.4	93,976	100.0
Total	184,810	86.8	28,217	13.2	213,027	100.0	364,573	86.6	56,421	13.4	420,994	100.0

Figure 3.11 shows the average export ratio by size categories. Here, large KIS firms tend to have higher share of exports from their sales volume. This result is supported by findings from Chapter 2, where larger firms have a higher probability to export than smaller firms, due to economies of scale and internal capabilities, but also, small firms sometimes resort to export to overcome underperformance on local markets and other external factors (Hirsch and Lev, 1971; Hirsch and Adar, 1974). Also, according to Tether and Hipp (2002), KIS tend to invest more in ICT, which may ease the capability of KIS to export their services abroad. Anyhow, these results reinforce the argument that larger firms export more than smaller firms.



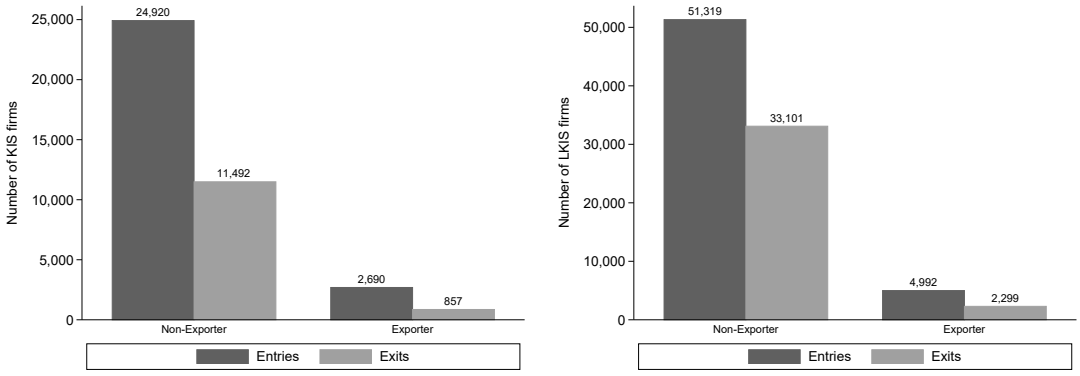
(a) KIS **(b)** LKIS

Figure 3.11: Average export ratio by knowledge-intensity and size category (whole sample).

Figure 3.12 presents the dynamic of entries and closures for exporters and non-exporters. Here, the results do not provide substantial conclusions. Since there is more non-exporters than exporters, the dynamic of entries and closures is more noticeable for non-exporters, suggesting that usually the decision of exporting comes after entering the market.

3.3.8 Summary Statistics

Table 3.16 shows the summary statistics by knowledge-intensity of the whole sample. In terms of duration, both types of firms have approximatively the same mean with equal variability, with LKIS average age slightly lower than KIS average age. In terms of duration, both type of firms have approximatively the same mean with equal variability, with LKIS average age slightly lower than KIS average age. As



(a) KIS **(b)** LKIS

Figure 3.12: Entries and exits of firms by knowledge-intensity and export category (whole sample).

for size, LKIS firms are, in average, larger than KIS firms, with superior variability for KIS firms. The scenario is similar for start-up size, since LKIS firms, in average, enter the market in larger scale than KIS firms, with a larger variability for KIS firms than LKIS firms. The amount of sales is much higher for LKIS firms, due to the superior number of LKIS firms with high sales volumes in the service industry, such as, e.g., wholesale and retail firms. The same pattern occurs to the average sales per employee and growth rate, with equally higher variability for LKIS firms, probably for the same reason. The average

Table 3.16: Summary statistics (whole sample).

	KIS	LKIS
Age [years]	4.14	4.13
	(2.69)	(2.70)
Size [number of employees]	3.44	3.60
	(20.47)	(12.00)
Start-up size [number of employees]	1.98	2.47
	(9.21)	(4.37)
Sales [10^3 €]	185.29	345.26
	(1804.42)	(3580.06)
Sales per employee [10^3 €/employee]	53.04	92.58
	(292.19)	(543.88)
Growth rate [%]	1.49	3.06
	(120.72)	(248.24)
Growing (dummy variable)	0.61	0.60
	(0.49)	(0.49)
Innovation expenditure [10^3 €]	19.96	19.44
	(960.18)	(329.76)
Innovation ratio [%]	57.73	69.70
	(3201.72)	(3399.13)
Innovator (dummy variable)	0.51	0.49
	(0.50)	(0.50)
Total exports [10^3 €]	27.85	49.02
	(749.22)	(2823.49)
Export ratio [%]	5.57	5.00
	(20.23)	(19.31)
Exporter (dummy variable)	0.13	0.13
	(0.34)	(0.34)
Number of observations	277,792	573,356
Number of firms	69,604	154,592
Number of closures	16,537	49,734
Proportion of closures [%]	24	32

Note: Mean and standard deviation (in parentheses).

innovation expenditure is slightly superior for KIS than LKIS firms. However, in terms of innovation ratio, LKIS firms have higher values than KIS firms. Probably LKIS firms have a need for more investment in innovation than KIS firms in order to survive. Furthermore, LKIS firms, in average, have a larger volume of exports revenue than KIS firms with superior variability but KIS firms have a slightly higher export ratio. Generally, most of the aggregated behaviour of service firms is aligned with the discussion in Chapter 2.

Chapter 4

Hypotheses and Methodology

In this Chapter, we introduce our set of hypotheses, based on the findings introduced in Chapter 2. Furthermore, we present econometric duration models as a tool for our study, due to its efficiency regarding survival analysis, since it utilises information of the whole firm's lifespan, rather than a single event in time (Mata and Portugal, 1999). To evaluate the importance and relevance of our hypotheses, we conduct a preliminary analysis through a non-parametric method, that computes survival rate estimates.

4.1 Hypotheses Definition and Preliminary Analysis

From findings discussed in Chapter 2, we gather relevant information regarding the factors that may influence firm survival. Since most studies refer to the manufacturing industry, and our study is focused on the service industry, we test most of the factors that seem feasible for our research. Therefore, we advance several hypotheses, to assess their impact on firm survival of our sample and, furthermore, the effect of each variable in KIS and LKIS firms, separately. We use a non-parametric method named Kaplan-Meier model[8], as an auxiliary tool to confirm the credibility and trustworthiness of the hypotheses proposed. From these results, we infer which variables are the most appropriate to include in our models. Note that even though the non-parametric estimates are unconditional, i.e., they cannot be interpreted as *ceteris paribus*, they allow us to see how the survival probability is different across groups.

4.1.1 Hypothesis 1 - Knowledge-Intensity

According with findings discussed in the literature, the education level of the general task force has a positive impact on firm's performance as the firm gets older and, consequently, a positive impact on firm's survival. Since the characterisation of the firm' sector according to knowledge-intensity is based on the degree and proportion of high education level workers, as referred on Section 2.2 and 3.1, we may test if knowledge-intensity has a positive impact on firm's survival as well. Therefore, we explore the following hypothesis and, to evaluate its relevance, we compute the Kaplan-Meier estimates.

[8]The Kaplan-Meier survival estimator is a non-parametric estimate of the survivor function $S(t)$, which is the probability of surviving past time t (Cleves et al., 2008), computed as follows: $\widehat{S(t)} = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j}\right), \ j = 1, \ldots, k$, where n_j is the number of individuals in risk at time t_j and d_j is the number of failures at time t_j. The result is a product of all observed failure times less than or equal to t.

Hypothesis 1: *Knowledge-intensive service firms have lower hazard of exit than less knowledge-intensive service firms.*

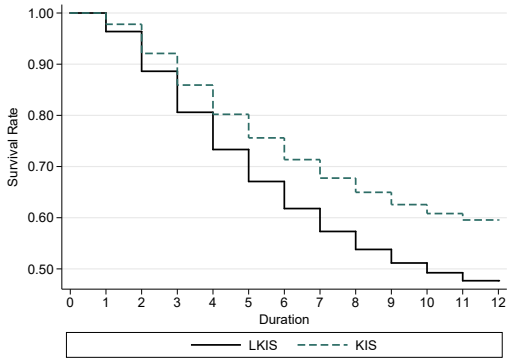


Figure 4.1: Kaplan-Meier survival estimates by knowledge-intensity.

Figure 4.1 shows a possible positive effect of this variable on firm survival. The survival rates of both KIS and LKIS firms appear to be similar on the first two years, however, they start to diverge. This suggests that knowledge-intensity is a factor to consider and, additionally, we may observe that KIS have a higher survival rates than LKIS, validating the importance of this hypothesis. To reinforce the study of these type of firms, we perform a similar test to the subsequent hypotheses, with an interaction of knowledge-intensity type with the corresponding variable. Since KIS firms have higher survival rates than LKIS firms, we presume that this leverage is triggered by some of the remaining determinants of survival. Therefore, our sub-hypotheses will imply a possible higher effect of the corresponding variable in KIS firms hazard of exit.

4.1.2 Hypothesis 2 - Age

Several studies suggests that age has a positive effect on hazard of exit, stating that younger firms are more vulnerable to exit the market than older firms, due to the initial period without profit and organisational settings issues (Wagner, 1994; Mata and Portugal, 1999; Dunne and Hughes, 1994; Evans, 1987a; Fritsch et al., 2006). Hence, to discuss a possible higher exposure to closure of young KIS firms, while comparing with young LKIS firms, we present the following hypotheses.

Hypothesis 2: *Firms that remains longer in the market have lower hazards of exit.*

Hypothesis 2.1: *Age has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*

According to Wagner (1994), entrants' hazard rates tend to increase during the first years and then decrease gradually over the years. This pattern is noticeable through Figure 4.2, since the hazard rate is inversely proportional to survival rate, namely, the survival rate decays with age at a rapid pace, and it slows down as the firm gets older. This result suggests that there is a positive influence of age on survival. Regarding knowledge-intensity interactions, through Figure 4.1. we observe some differences from the decay of hazard rates of KIS and LKIS firms. This may indicate a possible interaction between age and the type of firm.

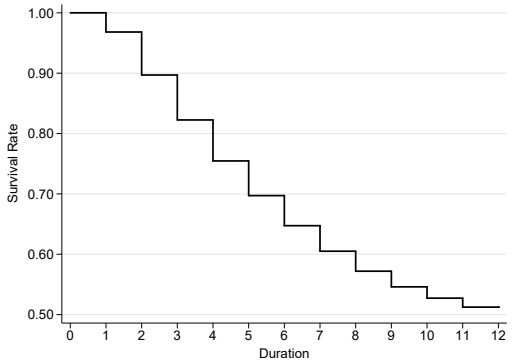


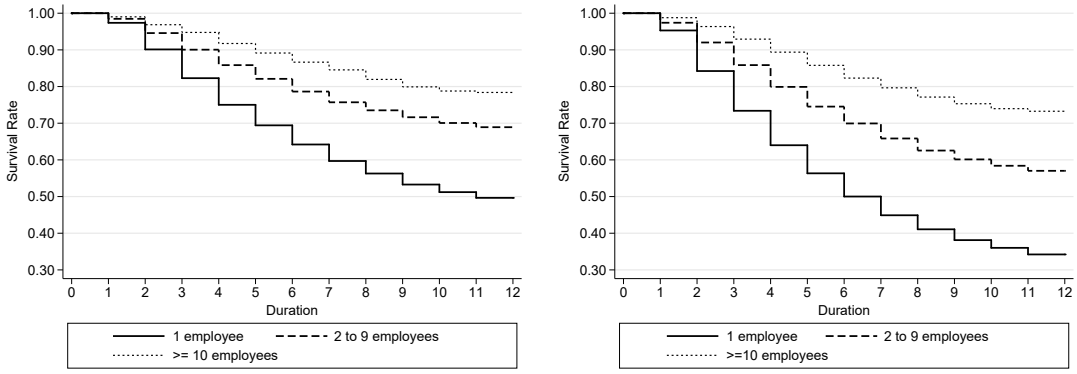
Figure 4.2: Kaplan-Meier survival estimates (whole sample).

4.1.3 Hypothesis 3 - Size

Findings from the literature review suggest that size and start-up size are important factors for firm survival, where the probability of survival increases with firm size, being small and young firms more vulnerable to leave the market (Dunne and Hughes, 1994; Evans, 1987a). Yet, these claims were made with samples mostly composed by manufacturing firms. According to Tether and Hipp (2002), service firms tend to be small due to efficiency purposes and, additionally, firms that are less intensive in knowledge are usually larger than firms more intensive in knowledge. Thus, we present the following hypotheses.

Hypothesis 3: *Larger firms have lower hazards of exit than smaller firms.*

Hypothesis 3.1: *Size has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*



(a) KIS **(b)** LKIS

Figure 4.3: Kaplan-Meier survival estimates by knowledge-intensity and size category.

We see that, according to Figure 4.3, size influences the non-parametric survival rates, since the two firm size categories with lowest number of employees (1 employee and 2 to 9 employees) present lower survival rates over time than the corresponding category with the highest number of employees ($\geq$ 10 employees). Furthermore, when analysing interactions with knowledge-intensity we notice that each firm size category present the same pattern observed in Figure 4.1: KIS has higher survival rates than

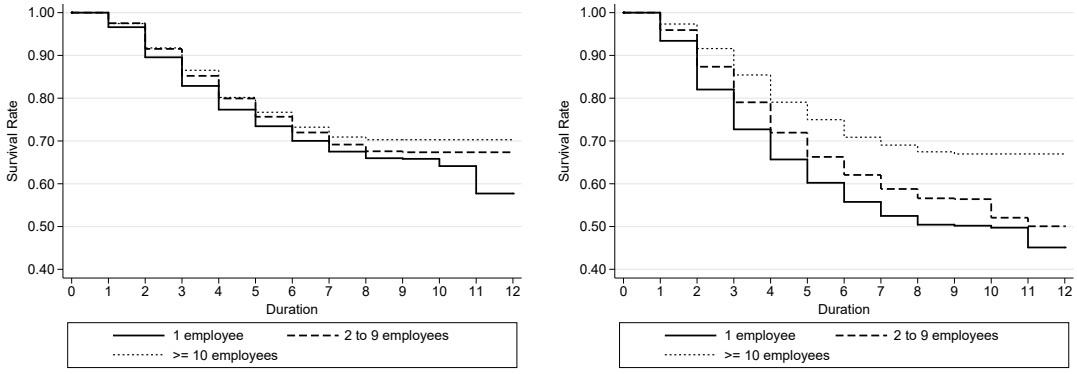
LKIS, which becomes more evident over the years. Also, the gap between survival rates of the different categories is higher for LKIS firms than KIS firms. This detail might indicate that the effect of size is more intense in LKIS firms, and not the opposite. However, we must bear in mind that our sample has limited information available about large firms, which may narrow our analysis accuracy.

4.1.4 Hypothesis 4 - Start-up Size

According to Evans (1987a) and Mata and Portugal (1994), large start-up size usually leads to higher chances of survival. Also, Mata et al. (1995) argue that entering the market in large scale indicates a greater expectation of success and increases the probability of survival. However, for the same reason as suggested in the last hypothesis, we check if these claims are necessarily true for our sample since, according to Tether and Hipp (2002), services firms tend to be smaller, being less intensive in knowledge larger than firms more intensive in knowledge. Thus, to understand the true value of start-up size on firm survival for the service industry, we explore the following hypothesis.

Hypothesis 4: *Large start-up size lowers the hazard of exit.*

Hypothesis 4.1: *Start-up size has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*



(a) KIS **(b)** LKIS

Figure 4.4: Kaplan-Meier survival estimates by knowledge-intensity and start-up size category.

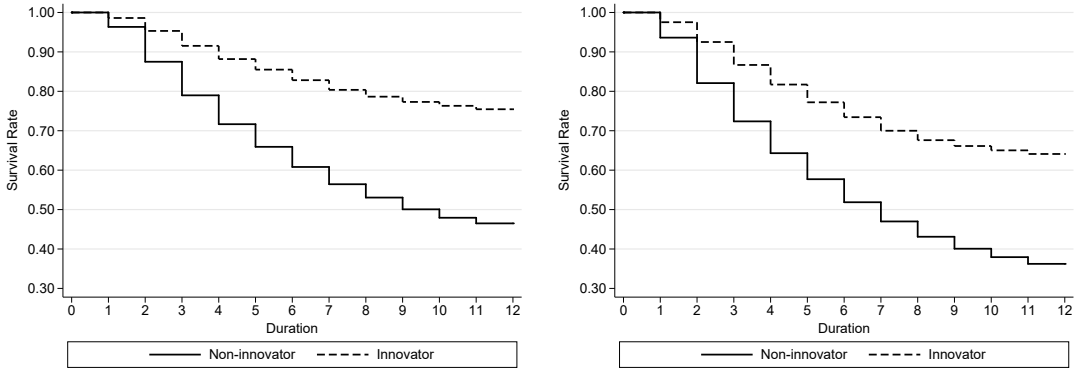
The shape and results from the graphs in Figure 4.4 suggest that LKIS firms with larger size at entry ($\geq$ 10 employees) have a higher likelihood to survive longer than those with a lower start-up size. However, this leverage seems to dissipate over time, since there is no significant difference between survival rates of the categories after being 8 years on the market. This result suggest that the upper-hand of entering the market with a significant number of employees may help LKIS firm survival in the first years but, as time passes by, other factors become more relevant for the upcoming years such as, for example, firm's efficiency (Dunne et al., 1988; Jovanovic, 1982). As for KIS firms, the result seems inconclusive and vague, which may indicate that entering in large scale is not particularly beneficial for KIS firms. Again, as we noticed in the last hypotheses regarding firm size, these results might be influenced by the limited data available about large firms in our sample.

4.1.5 Hypothesis 5 - Innovation

According to Cefis and Marsili (2006), innovation has a significant and positive effect in the likelihood of survival, particularly to younger firms, since this group is the most exposed to the risk of leaving the market and, consequently, benefit the most of innovation to survive (Cefis and Marsili, 2005, 2006). However, studies also show that innovation investment has a more unstable effect on younger firms than older firms, since the returns on investment are more unpredictable and riskier, due to the higher amount of financial requirements at early age (Coad et al., 2016). Also, empirical studies suggest that innovation have a particular significance on KIS firms and firm survival, in general. KIBS firms, a subgroup within the KIS firms, play a role as innovation intermediaries, being responsible of introducing innovation to the market (Tether and Hipp, 2002; Miles, 2008; Miles et al., 1995). Therefore, we postulate the follow hypotheses.

Hypothesis 5: *Innovators have lower hazard of exit than non-innovators.*

Hypothesis 5.1: *Innovating has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*



(a) KIS **(b)** LKIS

Figure 4.5: Kaplan-Meier survival estimates by knowledge-intensity and innovation category.

We may conclude from the survival rates estimates of Figure 4.5 that innovation influences the probability of survival. Also, we observe higher decays on the survival rate in the first years for non-innovators than innovators, supporting the findings from Cefis and Marsili (2006), which states that young firms benefit the most from innovation. Later on, the gap between innovators and non-innovators on the survival rate becomes clearer over the years, implying that it is still a relevant factor to older firms. While accounting the differences between KIS and LKIS firms, the estimates suggest that innovation factor has a stronger effect on survival than knowledge-intensity, since innovators have higher survival rates than non-innovators, with KIS firms having a small advantage over LKIS firms.

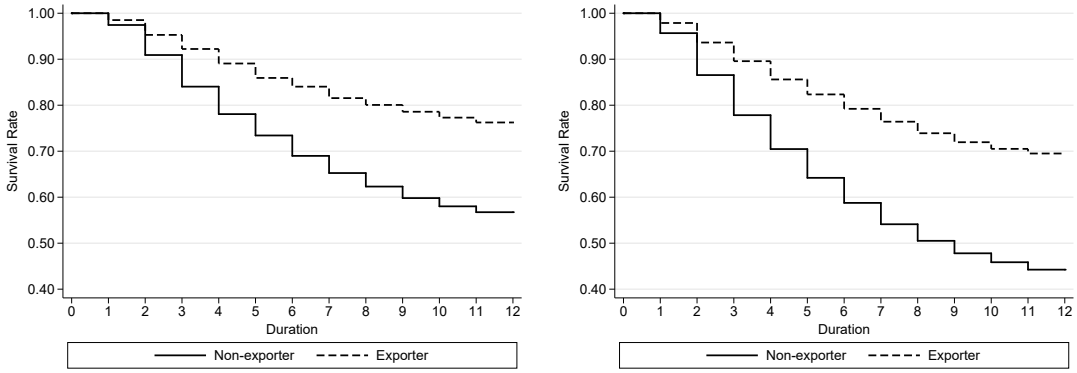
4.1.6 Hypothesis 6 - Exports

International trade may boost firm performance, since exporters are better performers than non-exporters (Bernard et al., 1995). Moreover, exports is a source to overcome underperformance and

possible other external factors that may jeopardize firm's growth and consequently, the firm's permanence in the market (Hirsch and Lev, 1971; Hirsch and Adar, 1974). Therefore, we present the following hypotheses.

Hypothesis 6: *Exporters have lower hazard of exit than non-exporters.*

Hypothesis 6.1: *Exporting has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*



(a) KIS **(b)** LKIS

Figure 4.6: Kaplan-Meier survival estimates by knowledge-intensity and export category.

From the Kaplan-Meier estimates in Figure 4.6, we see that exporting has a positive influence on survival. As before, the survival rate decreases more rapidly for non-exporters than for exporters. When observing the effect of knowledge-intensity, we see that exports prevails as a dominant factor, i.e., exporters have better prospects of survival than non-exporters, with a small leverage from KIS firms.

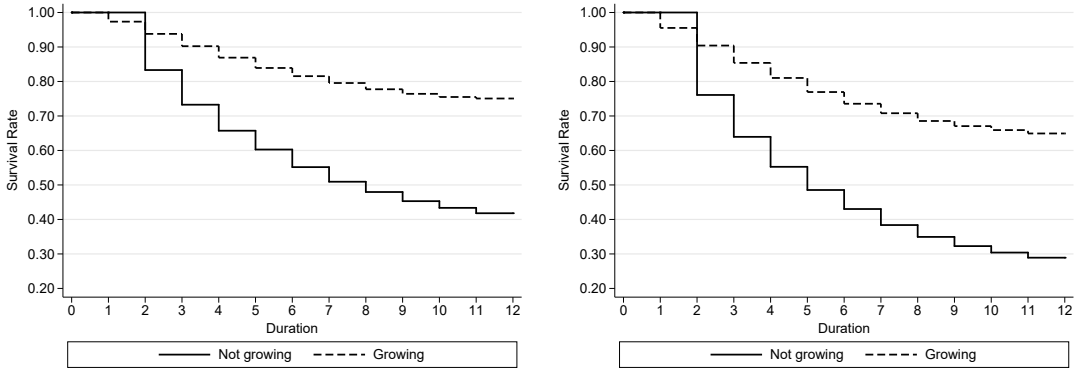
4.1.7 Hypothesis 7 - Growth Rate

High growth rates are usually associated to better prospects of survival (Audretsch, 1995). Moreover, younger firms have higher and more inconsistent growth rates than older firms, due to the process of learning their true efficiency, which may be achieved or not (Jovanovic, 1982). The aim of these further hypotheses is to capture the effect of productivity growth rate on survival, in terms of sales per employee and possible interaction with knowledge-intensity.

Hypothesis 7: *Growing firms, in terms of sales per employee, have lower hazards of exit.*

Hypothesis 7.1: *Growing, in terms of sales per employee, has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*

We may notice through Figure 4.7, that not growing, in terms of sales per employee, has a strong negative effect on the survival rate, which starts to decay more rapidly than firms that are growing. We also concluded, in Chapter 2, that firm growth decreases with age (Evans, 1987a). This may explain the steadiness of the survival rates at older age. Also, in the second year, we observe that not growing firms have slightly higher survival rates than growing firm. After this, the survival rates of not growing



(a) KIS **(b)** LKIS

Figure 4.7: Kaplan-Meier survival estimates by knowledge-intensity and growth rate.

firms starts to decline rapidly. This atypical behaviour is triggered by the fact that the continuous variable associated to growth rate was only computed after 2008, due to the absence of information related to sales prior 2007. We may conclude from this preliminary analysis that improving productivity per worker may boost greatly firm' survival in the first years of activity, however, this advantage fades over time. As usual, we perform a comparison between KIS and LKIS firms, where growth denote a stronger effect than knowledge-intensity.

Table 4.1 summarizes all the hypotheses explored and variables analysed in our models throughout this document.

Table 4.1: Set of hypotheses.

Variable	**Hypothesis Description**
Knowledge-intensity(KI)	H1: *Knowledge-intensive service firms have lower hazard of exit than less knowledge-intensive service firms.*
Age	H2: *Firms that remains longer in the market have lower hazards of exit.*
Age & KI	H2.1: *Age has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*
Size	H3: *Larger firms have lower hazards of exit than smaller firms.*
Size & KI	H3.1: *Size has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*
Start-up size	H4: *Large start-up size lowers the hazard of exit.*
Start-up size & KI	H4.1: *Start-up size has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*
Innovation	H5: *Innovators have lower hazard of exit than non-innovators.*
Innovation & KI	H5.1: *Innovating has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*
Exports	H6: *Exporters have lower hazard of exit than non-exporters.*
Exports & KI	H6.1: *Exporting has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*
Growth rate	H7: *Growing firms, in terms of sales per employee, have lower hazards of exit.*
Growth rate & KI	H7.1: *Growing, in terms of sales per employee, has a negative and higher effect on the hazard of exit of KIS firms than LKIS firms.*

4.2 Survival Analysis Overview

We employ a survival analysis method that aims to analyse, describe, explain or predict the occurrence and time of a certain event, the "death" of a firm. A typical solution to analyse these events in a multivariate dataset would be to use conventional statistical methods, such as the Ordinary Least Square Regression (OLS) model. However, OLS is often not suitable to handle duration models. Firstly, there is a problem regarding the residual's normal distribution assumption, which may be impractical when handling time to an event. Secondly, according to Mata and Portugal (1994), information regarding duration is usually incomplete and, most of the time, censored, which means that sometimes there will be no record of the occurrence of any events, implying that the event cannot be measured (Allison, 2010). This is a common problem while dealing with real data, since we may have a limited observation period, not long enough to detect the occurrence of a failure of all units of observation (Jenkins, 2005). Additionally, in duration analysis, it is common to have time-varying covariates, variables that change over time, and OLS does not easily handle this situation. Since standard estimation methods do not consider this problem, this may produce biased and inconsistent estimates, or even return negative predicted values, even though it is impossible in this type of study. Survival analysis methods are a solution for these problems since they can cope with possible non-symmetric distributions and properly handle right-censoring, among other details explained in the following sections (Jenkins, 2005).

4.2.1 Continuous versus Discrete-time Methods

Before selecting a specific model to work with, first, we must choose if we should treat the survival time as a continuous or a discrete random variable. In case that the exact time of the occurrence is known, the proper path is to use continuous-time methods. On the other hand, if we only have information related to the month or year of the event occurrence (i.e., a grouped interval of time units), it is more appropriate to use discrete-time methods, since we may face multiple events occurring in the same interval, without having information of the order of occurrence (Jenkins, 2005). This is the case of our sample: time is recorded in years and one time-unit represents a large proportion of the average age of firms (about four years). Thus, the unit of measurement is not small enough to consider time as continuous. However, since the results from continuous time models are in many cases similar to those obtained with discrete time models, are easier to interpret and most of the tools available in the software we use (Stata) for survival analysis are for continuous-time data, we chose to implement models from the continuous-time family.

4.2.2 Hazard and Survival Function

One of the main survival analysis' tools is the hazard function $h(t)$. In a continuous setting, the hazard function is described as the "instantaneous probability that the duration under study will end in an infinitesimally small time period u after time t, given that the duration has not elapsed until time t"

(Bhat, 1996). It may be written as described in Equation (4.1):

$$h\left(t\right)=\lim_{\mathrm{u}\to 0^{+}}\frac{P(t\ \leq\ T\ \leq\ t\ +\ u\mid T\ \geq\ t)}{u}=\frac{f\left(t\right)}{S\left(t\right)} \tag{4.1}$$

where T is the firm's life duration; $f\left(t\right)$ is the probability density function; and $S\left(t\right)$ is the survival function, which is the probability that the event's duration is at least t, and that the event by which the current event comes to an end occurs later than t (Blossfeld et al., 2012), i.e., the probability of surviving after t. The survival function may be written as described in Equation (4.2):

$$S\left(t\right)=\Pr\left(T\ >\ t\ \right)=1-\ F\left(t\right) \tag{4.2}$$

where $F\left(t\right)$ is the cumulative distribution function, also known as the failure function. The hazard function fully characterises the distribution of T, while showing at which rate the subject leaves the state at duration t, given that it did not exit it yet. Duration dependence plays a significant role on firm survival theory (Jovanovic, 1982). Duration dependence exists if $\frac{dh(t)}{dt}\neq 0$ holds, i.e., the hazard rate varies with time. We may interpret the hazard function derivative as follows (Heckman and Singer, 1984).

- If $\frac{dh(t)}{dt}>0$, at $t=t_0$, there is a positive duration dependence at t_0.
- If $\frac{dh(t)}{dt}<0$, at $t=t_0$, there is a negative duration dependence at t_0.

A commonly used form to model the hazard rate is the proportional hazards model, also known as "multiplicative hazard" or "log relative hazard" model. It may be written as shown in Equation (4.3):

$$h\left(t,X_i\right)=h_0\left(t\right)\lambda\left(X_i\right) \tag{4.3}$$

where $h_o\left(t\right)$ denotes what is called the baseline hazard function (used in parametric and semi-parametric methods), that summarises the pattern of "duration dependence"; $\lambda\left(X_i\right)$ is an individual-specific non-negative function of covariates X that scales the baseline hazard function, which is common to all individuals. Under this model, the covariates have multiplicative effects on the hazard function. The main reason for the usefulness of proportional hazards models is that, in real data, "covariates are often time-varying". Hence, the hazard function will be affected by the values of the covariates at a given point (Van den Berg, 2001), and we may observe these effects through these models.

4.2.3 Parametric, Non-parametric and Semi-parametric Approach

We must also decide on a functional form for the baseline hazard function that properly fits our data, in terms of how intense the collateral effects of the explanatory variables are, and how it is possible to control them (Heckman and Singer, 1984). For that purpose, there are three main approaches:

- **Parametric models** - in this type of models, we have to assume a proper distribution of the survival times, i.e., we must choose the baseline hazard function. Some possible parametric models could be the exponential, Weibull, log-logistic, among others. Given that, in general, the literature provides no indication on the shape of the distribution of the hazard of market exit for firms, and since an incorrect specification of the baseline hazard distribution may cause problems in the estimation,

one must exercise additional care when estimating these models.

- **Non-parametric models** - this approach does not consider how the covariates may influence the probability that a subject will fail. Some of the most common non-parametric regression methods, such as local polynomial regression, do not adequately deal with censoring. Methods like the Kaplan-Meier or Nelson-Aalen estimators are the most commonly used to non-parametrically estimate the likelihood of survival and are capable of accommodating censoring properly (Cleves et al., 2008).
- **Semi-parametric models** - combines the best features of each approach mentioned above. It allows for the estimation of the relationship between the hazard rate and the explanatory variables (unlike the non-parametric methods), without making assumptions about the shape of the baseline (unlike the fully-parametric models). It has several advantages. By fitting an unspecified baseline hazard function into the proportional hazard model, it is possible to obtain robust estimates by analysing the influence of covariates on the outcome. Additionally, since theories in social sciences rarely present strong arguments to use a specific parametric model, this model can be a good alternative to the parametric models.

To aid the choice of the model to estimate, we perform a preliminary analysis of our dataset using a non-parametric method to describe our sample. For that purpose, we use Kaplan-Meier survival estimates as an auxiliary tool to observe the validity of the hypotheses described in Section 4.1. As for the remaining study, a better fit to our analysis should be a semi-parametric method, using a proportional hazard method. For that matter, we consider the choice between two models: Cox's proportional hazards model and the piecewise-constant exponential (PCE) model.

4.2.4 Cox Proportional Hazard Model

The most commonly method used is the Cox model. With this model, we can estimate covariates' effects but not the hazard baseline function itself, through a partial-likelihood framework. It may be written as shown in Equation (4.4):

$$h\left(t, X\right) = h_0\left(t\right) \exp\left(X\left(t\right)\beta\right) \tag{4.4}$$

The hazard rate, $h\left(t, X\right)$, is the product of an unspecified baseline rate, $h_0\left(t\right)$, and a second term exposing the possible influences of a covariate vector $X\left(t\right)$ and the respective vector of parameters β on the hazard rate. This model is a special case of the proportional hazard's family. We can estimate the separate (conditional) proportional effects of covariates on the transition rate without changing the hazard function shape. Hence, the Cox model can only be used if this proportionality assumption is well justified (Blossfeld et al., 2012).

4.2.5 Piecewise-Constant Exponential Model

The PCE model is a form of proportional hazards model and, also, a simple generalisation of the standard parametric exponential model. It is helpful when the form of the time-dependence of the process is unknown. The main idea is to split the time axis into smaller time intervals and assume that the

hazard rate is constant in each interval, but also allowing the rate to change across the different intervals (Jenkins, 2005). Generically, it may be written as shown in Equation (4.5):

$$h\left(t, X_t\right) = \begin{cases} {h'}_1 \lambda_1 & t \in [0, \tau_1] \\ {h'}_2 \lambda_2 & t \in [\tau_1, \tau_2] \\ ... & \\ {h'}_k \lambda_k & t \in [\tau_{k-1}, \tau_k] \end{cases} \tag{4.5}$$

where the baseline hazard rates (h'_k) are constant within each interval k, but may be different between intervals, while λ_k is an individual-specific non-negative function of covariates X_t. The Cox and the PCE models are very similar in certain aspects. They are both flexible in terms of the shape of the hazard function and both may incorporate time-varying covariates. However, the PCE model requires some specification from the researcher regarding the cut points for the intervals and, on the other hand, the Cox model's estimates come from a totally arbitrary baseline hazard function. Hence, Cox model is more general but, if we want flexibility and explicit estimates of the baseline hazard function, we should use the PCE model.

4.2.6 Final Choice

Recent literature presents no evidences or suggestions regarding the distribution of time to failure, which is an indicator for the best baseline for our model. Moreover, one of the hypotheses proposed is related with the role of duration dependence on survival, i.e., the effect of age on survival, which is not possible with Cox semi-parametric approach. Thus, our choice lies on the piecewise-constant exponential model. For robustness purposes, we also run Cox models, to compare the estimated coefficients and verify if they are similar, in order to avoid a misparameterised baseline hazard (Cleves et al., 2008).

Chapter 5

Results

In this Chapter we present the results from our econometric analysis and discuss the main findings and limitations of our study. We chose the piecewise-constant exponential model due to its flexibility and the possibility to explicitly estimate the baseline hazard function. To analyse the hypotheses, we compute the average marginal effects on hazard rates, with models that include the determinants of firm survival. Further on, we study the interaction of these determinants with knowledge-intensity (KIS firms versus LKIS firms). To use the PCE model, we first must decide which time intervals to use. For that matter, we based our cut points on the firm's distribution according to age, observed in Figure 3.5. To analyse innovation and exports, we decide to use the corresponding dummy variables due to the heterogeneous firm sample, in terms of sector and size scale. Same applies to the growth rate dummy variable, where we characterise firms that grow or not according to the sign (negative or positive) of the corresponding continuous variable. We experiment other methods such as Cox and Weibull, for robustness sake, and find similar results. Also, to account with external and macroeconomic conditions, all models are controlled by region, unemployment rate and gross domestic product (GDP) per capita.

5.1 Effect on Hazard Rate Analysis

Marginal effects are an effective way of analysing the impact of variables in non-linear models (Williams, 2012). Thus, we proceed to interpret the influence of the firm survival determinants on the hazard rate through average marginal effects. It can be interpreted as the absolute change on the hazard rate in percentage points (p.p.), i.e., it measures the effect on the conditional mean of y of changes in one of the regressors x_j, while keeping all other covariates constant. A positive marginal effect means that increasing x_j is associated with higher hazard rates and shorter survival times, whereas a negative marginal effect means that increasing x_j is associated with lower hazard rates and longer survival times. We must acknowledge that we are dealing with average values and these results may not translate clear conclusions regarding the real effect of these variables. Surviving firms contribute more observations to the sample, thus, their influence may overestimate the real impact of the determinants of firm survival. Therefore, we compared the results from the whole sample with the results from the last year of observations of each firm and the first year of observations of each firm. Since we did not detect any

significant difference, we decide to analyse the average marginal effects from the whole sample.

5.1.1 Average Marginal Effects

Table 5.1 presents the average marginal effects of six models with the variables related to the set of hypotheses: age, type of industry (KIS or LKIS), growth rate, size, start-up size, innovation and exports. In model 1, we present the impact of size and start-up size categorically. In model 2, we use the logarithm form on size and start-up size to impose a constant percentage effect of both variables on the marginal effect, i.e., it allows us to interpret the impact of 1% increase of size/start-up size on the hazard rate without worrying about firm size scale issues. Models 3, 4, 5 and 6 were developed to analyse the role of size and start-up size separately due to collinearity, i.e., high correlation observed

Table 5.1: Average marginal effects (whole sample).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
KIS	-0.028***	-0.028***	-0.027***	-0.026***	-0.027***	-0.027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Age:						
3 to 4 years	-0.029***	-0.029***	-0.031***	-0.031***	-0.014***	-0.014***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
5 to 6 years	-0.051***	-0.051***	-0.052***	-0.053***	-0.031***	-0.032***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0011)
$\geq$ 7 years	-0.063***	-0.063***	-0.064***	-0.065***	-0.053***	-0.054***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0009)	(0.0009)
Size:						
2 to 9 employees	-0.054***					-0.033***
	(0.0011)					(0.0006)
$\geq$ 10 employees	-0.073***					-0.045***
	(0.0018)					(0.0013)
Log of size		-0.050***			-0.026***	
		(0.0009)			(0.0005)	
Start-up size:						
2 to 9 employees	0.031***			-0.004***		
	(0.0011)			(0.0008)		
$\geq$ 10 employees	0.066***			-0.011***		
	(0.0066)			(0.0026)		
Log of start-up size		0.032***	-0.0049***			
		(0.0009)	(0.0006)			
Innovator	-0.044***	-0.042***	-0.052***	-0.052***	-0.040***	-0.042***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Exporter	-0.030***	-0.029***	-0.033***	-0.033***	-0.031***	-0.031***
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Growing	-0.105***	-0.107***	-0.099***	-0.099***	-0.082***	-0.082***
	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
Number of observations	460,242	460,242	460,242	460,242	632,893	632,893
Number of firms	142,534	142,534	142,534	142,534	198,859	198,859
Log likelihood	-71,838	-71,537	-73,181	-73,207	-99,841	-99,960
p-value of the log likelihood test	0.000	0.000	0.000	0.000	0.000	0.000

Note: Standard errors in parentheses. All models control for sector, region, unemployment rate and GDP per capita. For categorical variables, base levels are not presented (age = 1 to 2 years; start-up size = 1 employee; size = 1 employee; non-innovator; non-exporter; not growing). *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

between size and start-up size ($\rho = 0.72$). Variables such as age, innovation, exports and growth rate are present in all models. The difference between the number of observations of each model is related to the information available of start-up size, innovation, exports and growth rate variables. All marginal values are statistically significant, which means that we may rely on these results for further conclusions.

We find that KIS firms have significantly lower hazards of exit (about 2.75 p.p. lower across all models) than LKIS firms, while holding all other variables constant. This result is aligned with hypothesis 1 and earlier Kaplan-Meier results, in Chapter 4. The estimates also show that older firms present lower and statistically significant hazard ratios than younger firms, since the marginal effects values are negative and decreasing as the age category increases, supporting hypothesis 2.

As for firm size (number of employees), we may observe from model 1 and 6 that the marginal effects value are negative, getting lower with higher size categories and, from model 2 and 5, the marginal effect values for the logarithm of size are negative, indicating that firm size lowers the hazard rate. These results are aligned with the majority of studies in the literature, that show a higher exposure to exit for small firms and a more stable and secure stay in the market for large firms (Dunne and Hughes, 1994; Evans, 1987a).

While analysing firm start-up size (number of employees in the first year of activity), we have different results throughout our models. In model 1 and 2, where both size and start-up size are present in the model, the corresponding marginal effect for the categorical and logarithmic start-up size variable are positive. According to these results, having a large size at the beginning of the firm's activity may seem to harm the chances of survival, which is counter-intuitive and against what was discussed in the literature. However, in models where size is not included (model 3 and 4), the marginal effects are negative and decreasing, which is more coherent with the literature. Probably the high correlation between size and start-up size did influence the results from model 1 and 2. Nevertheless, this result suggests that start-up size may lead to higher prospects of survival, in agreement to studies from Chapter 2 (Mata et al., 1995; Mata and Portugal, 1994).

The estimates also suggest that innovators have lower hazard ratios than non-innovators, where the marginal effects from being an innovator are negative (- 5 to - 4 p.p.) throughout all models, confirming hypothesis 5. Same applies to exports, where exporters have less 2.9 to 3.3 p.p on the hazard rate than non-exporters, supporting hypothesis 6. Also, being more efficient and productive, i.e., having a positive growth rate in terms of sales per employee, seems to have a positive impact on survival, since growth in terms of sales per employee lowers the hazard rates in 8.2 to 10.7 p.p., confirming hypothesis 7.

5.1.2 Average Marginal Effects by Knowledge-Intensity

Table 5.2 shows the average marginal effect of the firm survival determinants by knowledge-intensity, i.e., for KIS and LKIS firms. We chose model 1, 2, 3 and 4 due to the different results caused by high correlation between size and start-up size. We may notice that all marginal values are statistically significant. However, we have to check if we can rely on those results, i.e., the confidence intervals may not intercept with each other. If they do not intercept, we may conclude the existence of different effects on KIS and LKIS firms, at 95% level of confidence. Otherwise, we may not conclude differences

Table 5.2: Average marginal effect by knowledge-intensity with interactions (whole sample).

	Model 1	Model 2	Model 3	Model 4
Age: 3 to 4 years				
LKIS	-0.033***	-0.033***	-0.034***	-0.035***
	[-0.036, -0.031]	[-0.035, -0.030]	[-0.037, -0.032]	[-0.037, -0.032]
KIS	-0.022***	-0.022***	-0.023***	-0.024***
	[-0.024, -0.020]	[-0.024, -0.020]	[-0.025, -0.022]	[-0.025, -0.022]
Age: 5 to 6 years				
LKIS	-0.058***	-0.058***	-0.059***	-0.060***
	[-0.061, -0.056]	[-0.061, -0.056]	[-0.062, -0.057]	[-0.062, -0.057]
KIS	-0.039***	-0.038***	-0.040***	-0.040***
	[-0.040, -0.037]	[-0.040, -0.037]	[-0.042, -0.038]	[-0.042, -0.038]
Age: $\geq$ 7 years				
LKIS	-0.072***	-0.072***	-0.073***	-0.073***
	[-0.075, -0.070]	[-0.075, -0.069]	[-0.076, -0.070]	[-0.076, -0.070]
KIS	-0.048***	-0.048***	-0.050***	-0.050***
	[-0.050, -0.046]	[-0.050, -0.046]	[-0.052, -0.047]	[-0.052, -0.047]
Size: 2 to 9 employees				
LKIS	-0.061***			
	[-0.064, -0.060]			
KIS	-0.039***			
	[-0.042, -0.036]			
Size: $\geq$ 10 employees				
LKIS	-0.085***			
	[-0.089, -0.081]			
KIS	-0.053***			
	[-0.059, -0.046]			
Log size				
LKIS		-0.059***		
		[-0.062, -0.057]		
KIS		-0.034***		
		[-0.037, -0.031]		
Start-up size: 2 to 9 employees				
LKIS	0.032***			-0.008***
	[0.029,0.035]			[-0.010, -0.006]
KIS	0.031***			0.004***
	[0.027,0.034]			[0.002,0.007]
Start-up size: $\geq$ 10 employees				
LKIS	0.066***			-0.018***
	[0.051,0.082]			[-0.024, -0.012]
KIS	0.081***			0.010*
	[0.049,0.113]			[-0.001,0.021]
Log of start-up size				
LKIS		0.035***	-0.009***	
		[0.033,0.037]	[-0.010, -0.007]	
KIS		0.029***	0.004***	
		[0.026,0.032]	[0.002,0.006]	
Number of observations	460,242	460,242	460,242	460,242
Number of firms	142,534	142,534	142,534	142,534
Log likelihood	-71,838	-71,537	-73,181	-73,207
p-value of the log likelihood test	0.000	0.000	0.000	0.000

Note: 95% confidence intervals in brackets. All models control for sector, region, unemployment rate and GDP per capita. For categorical variables, base levels are not presented (age = 1 to 2 years; start-up size = 1 employee; size = 1 employee; non-innovator; non-exporter; not growing). *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 5.2: Average marginal effect by knowledge-intensity with interactions (whole sample) (continued).

	Model 1	Model 2	Model 3	Model 4
Innovator				
LKIS	-0.047***	−0.043***	-0.055***	-0.056***
	[-0.049, -0.045]	[-0.045, -0.041]	[-0.057, -0.054]	[-0.058, -0.054]
KIS	-0.040***	-0.040***	-0.046***	-0.046***
	[-0.043, -0.038]	[-0.042, -0.038]	[-0.049, -0.044]	[-0.048, -0.044]
Exporter				
LKIS	-0.034***	-0.0332***	-0.0376***	-0.0374***
	[-0.037, -0.032]	[-0.035, -0.031]	[-0.040, -0.036]	[-0.040, -0.035]
KIS	-0.023***	-0.022***	-0.025***	-0.025***
	[-0.024, -0.021]	[-0.023, -0.020]	[-0.027, -0.024]	[-0.027, -0.024]
Growing				
LKIS	-0.121***	-0.123***	-0.113***	-0.113***
	[-0.124, -0.119]	[-0.126, -0.120]	[-0.115, -0.110]	[-0.115, -0.110]
KIS	-0.079***	-0.080***	-0.076***	-0.076***
	[-0.081, -0.076]	[-0.082, -0.077]	[-0.078, -0.074]	[-0.078, -0.073]
Number of observations	460,242	460,242	460,242	460,242
Number of firms	142,534	142,534	142,534	142,534
Log likelihood	-71,838	-71,537	-73,181	-73,207
p-value of the log likelihood test	0.000	0.000	0.000	0.000

Note: 95% confidence intervals in brackets. All models control for sector, region, unemployment rate and GDP per capita. For categorical variables, base levels are not presented (age = 1 to 2 years; start-up size = 1 employee; size = 1 employee; non-innovator; non-exporter; not growing). *Significant at 10%, ** Significant at 5%, *** Significant at 1%.

based on knowledge-intensity. For this analysis, we include interactions in our models according with findings from the literature. Since innovation is a key player on firm survival, where KIS firms play a role of innovation carriers (Miles et al., 1995; Cefis and Marsili, 2005, 2006; OECD, 2006), and service firms tend to be small for efficiency purposes (Tether and Hipp, 2002), we include the following interactions in all four models: type of industry and innovation, type of industry and size; and type of industry and start-up size[9].

According to the estimates, firm age has a negative and higher impact on LKIS firms hazard rates than KIS firms hazard rates throughout all models. Also, the marginal effect values present the same pattern has the previous result, which decreases as the age category increases, with a higher decay on LKIS firm's values. None of the confidence intervals overlap, so we may trust these results.

While considering the different impact of size and start-up size in service firms, there are some distinct results to analyse. Firstly, there is no differences between KIS and LKIS firms when accounting with the effect of the start-up size categorical variable in the first model, since both confidence intervals overlap. However, in model 3 and 4 where the firm size is no longer present, the results are more reliable: the marginal values are negative for LKIS firms and positive for KIS firms (with non-overlapped confidence intervals), probably due to KIS firms tendency to start their business in small scale (Tether and Hipp, 2002). Regarding firm size, the results are consistent and reliable (the confidence intervals do not overlap) across all models: size has a negative effect on hazard rates, being more accentuated and beneficial for LKIS firms than KIS firms.

As for the impact of innovation, we identify a stronger effect in LKIS firms than KIS firms in model 1,

[9]The literature also indicates possible interactions between exports with size, innovation with growth, and innovation with size. We also computed the marginal effects including these interactions in different models for robustness sake. However, we did not consider them relevant to our case since none of them were statistical significant.

3 and 4[10]. While considering the impact of exports, we find that being exporter has a higher average effect in LKIS than KIS firms across all models, with non-overlapping confidence intervals. Also, LKIS firms able to grow in terms of sales per capita appear to have an upper-hand to not growing LKIS firms, since the marginal impact of "growing" is superior to the one observed in KIS firms. For this variable, the confidence interval do not intercept, so, we may confirm that these differences are statistically significant.

Table 5.3 summarizes the results from this study.

Table 5.3: Summary of the results.

Hypothesis	**Results**
H1 - Knowledge-intensity(KI)	KIS firms hazard $<$ LKIS firms hazard
H2 - Age	Old firms hazard $<$ Young firms hazard
H3 - Size	Large firms hazard $<$ Small firms hazard
H4 - Start-up size	Entry in larger scale hazard $<$ Entry in smaller scale hazard
H5 - Innovation	Innovators hazard $<$ Non-innovators hazard
H6 - Exports	Exporters hazard $<$ Non-exporters hazard
H7 - Growth Rate	Growing firms hazard $<$ Not growing firms hazard
H2.1 - Age & KI	Age effect in LKIS firms hazard $>$ Age effect in KIS firms hazard
H3.1 - Size & KI	Size effect in LKIS firms hazard $>$ Size effect in KIS firms hazard
H4.1 - Start-up size & KI	Start-up size effect in LKIS firms hazard $>$ Start-up size effect in KIS firms hazard
H5.1 - Innovation & KI	Innovation effect in LKIS firms hazard $>$ Innovation effect in KIS firms hazard
H6.1 - Exports & KI	Export effect in LKIS firms hazard $>$ Export effect in KIS firms hazard
H7.1 - Growth Rate & KI	Growing effect in LKIS firms hazard $>$ Growing effect in KIS firms hazard

5.1.3 Discussion

All the hypotheses concerning the determinants of firm survival were confirmed. Even with problems concerning collinearity, it was possible to observe the impact of start-up size in firm survival, resorting to models without the variable related to the current size of the firm. All marginal effects from the remaining variables present coherent results with the literature review. When accounting the sub-hypotheses, the estimates show the opposite expected scenario where, generally, LKIS firms benefit more from the impact of the firm survival determinants than KIS firms.

Hypothesis 1, related with knowledge-intensity, was confirmed by our estimates. The fact that knowledge-intensity has a negative effect on hazard rates may be related with the proportion of educated workers and the demand for the KIA activities involved progressively increasing. According to Brüderl et al. (1992), the number of experienced workers increase the chances of survival and highly educated workforce tend to raise sales productivity. Thus, we suggest that part of the reason for lower hazard of exit on KIS firms may rely on human capital. Moreover, there is a number of studies that relate KIBS firms, an important subset of KIS firms, to the diffusion of innovation in the market, with a crucial role on innovation processes (OECD, 2006; Tether and Hipp, 2002; Muller and Zenker, 2001). The exchange of knowledge and interactivity occurred between KIBS firms and client firms may promote mutual growing, being beneficial for both parties (Muller and Zenker, 2001; OECD, 2006). These benefits lead to an increase on the demand of KIA services, which may improve the prospect of survival. On

[10]In model 2, the 95% confidence intervals do overlap. However, they do not overlap at 90% level of confidence, thus, we may confirm statistically significant differences between the effect of innovation in KIS and LKIS firms at a 90% level of confidence.

the other hand, LKIS firms provide services that are more standard and easily reproducible, which may induce into less barriers of entry, turning their markets more competitive[11]. This scenario may turn LKIS firms more vulnerable to closure than KIS firms.

Hypothesis 2, related with age, was confirmed. According to the decreasing values of marginal effects throughout the categories of age, we conclude that staying in the market lowers the hazard of exit. This is a common result to studies related to firm age. However, we must be careful while studying the true meaning of this variable. Firstly, age or passage of time per se may not improve the probability of survival. What is implied in this variable is the experience and know-how gained as the firm stays longer in the market. As Jovanovic (1982) selection theory suggest, firms only survive if they become aware of their efficiency levels and cost structures. Another reason may lie on the implications of unobserved heterogeneity (often referred as frailty in the survival analysis context). When we do not account for this issue, the non-frailty model will over-estimate (under-estimate) the degree of negative (positive) duration dependence in the baseline hazard (Jenkins, 2005). Since this is a detail that is not considered in our models, the effect of age might be over-estimated. The results related with sub-hypothesis 2.1, i.e., interaction between age and knowledge-intensity typology, indicate that age has more influence on the survival of LKIS firms than KIS firms, and the effect gets stronger for LKIS firms between age categories. Since LKIS firms are more labour intensive, staying in the market may provide them some advantage in comparison to their younger competitors. Due to the higher standardisation and labour-intensity from LKIS firms (Tether and Hipp, 2002), gains in efficiency may have a higher impact in LKIS firm's performance, as the firm gets older. Perhaps for KIS firms, gains in efficiency are more dependable of other factors such as the quality and adequacy of the general workforce qualification, that may or may not be achievable with age.

Hypothesis 3, related with size, was confirmed by the estimates. This is aligned with the literature, where small firms have higher vulnerability to exit than large firms. According to Headd (2003), large firms are more stable and have access to better financing tools, which improves the probability of survival, while smaller firms are more constrained financially, perhaps turning into an additional barrier for growth and survival. On the other hand, smaller firms tend to invest more and take less debt, improving their prospects of survival (Cooley and Quadrini, 2001). When accounting with the impact on KIS and LKIS hazard rates (sub-hypothesis 3.1), firm size has a superior and negative effect on LKIS hazard rates, as we may observe from model 1 and 2 from Table 5.2. This might be related to the fact that LKIS firms activities are more labour intensive and require more workers, while KIS firms activities require qualified employees, not necessarily in larger scale. Plus, some KIS firms struggle to hire workers with the right set of skills and qualifications for the job, due to the low share of highly educated people in Portugal. Additionally, acquiring several high skilled employees is an additional expense for the firm due to higher salaries. For instance, Silva and Lima (2017) argue that high-tech firms values human capital more than low-tech firms due to difficulty in acquiring high skill workers able to perform complex tasks of the respective firm's activities, and also as an incentive to retain workers in the company. Thus, this

[11] We confirmed differences between the market concentration (Herfinfahl-Hirschman Index — HHI) of KIS and LKIS firms. According to our sample, in average, LKIS markets (HHI = 221) are less concentrated than KIS markets (HHI = 412). These values were calculated by year, region and sector.

may influence the decision of remaining small, for efficiency purposes.

Hypothesis 4, related to start-up size, was confirmed in model 3 and 4, where the current size was not included. Under those conditions, start-up size seems to improve the prospects of survival. This determinant is also mentioned in the literature, where starting the business with a considerable large size indicates higher expectation of success and likelihood of survival (Mata and Portugal, 1994; Evans, 1987a; Brüderl et al., 1992). While considering knowledge-intensity (sub-hypothesis 4.1), there is a negative effect on hazard rates for LKIS firms, while for KIS firms the effect is positive. Here, the justification behind these results is similar to the one related to firm size: KIS firms tend to perform under smaller scale due to the requirements of their internal activities and lowering additional costs, since they are more intensive in knowledge; and LKIS firms benefit more from economies of scale since their activities are more labour intensive (Tether and Hipp, 2002). However, these results may not translate the real influence of start-up size on the long term. As seen in the Kaplan-Meier estimates (Figure 4.4), the advantage of starting the business at larger scale starts to dissipate after 8 years in the market. Since we are dealing with average values of the whole sample, the lack of impact from start-up size in the last years of observations could lower the average marginal values. This is aligned with a study from Audretsch (1991), where it says that the existence of economies of scale and high capital labour tend lower the probability of survival for an uncertain period of time. Also, Agarwal and Audretsch (2001) suggest that this advantage provided by large size entry varies with product life cycle and/or technological intensity of the industry. According to their study, size and high R&D expenses are not crucial in high-tech industry. Instead, being able to identify a niche marketing strategy is more beneficial in terms of survival in the long term.

Hypothesis 5 concerns with the effect of innovation in firm survival. In line with findings from Chapter 2, all models were consistent with the negative effect that innovation has on hazards of exit. Several findings indicate that innovation has a strong and positive impact on performance and profitability, leading to longer stays in the market (Audretsch, 1991, 1995; Mansfield, 1962). Also, young and small firms may benefit greatly from innovation, even though it carries some risk to invest capital at early age (Coad et al., 2016). Innovation can be a tool to overcome possible scale and/or size disadvantages that young and smaller firms may face at entry (Geroski, 1995; Audretsch, 1995). Moreover, innovators tend to have higher growth rates on sale, which improves the likelihood of survival (Audretsch, 1991). As for the effect on KIS and LKIS firms (sub-hypothesis 5.1), it seems that innovation has a stronger and negative effect in LKIS firms hazard rates than KIS firms hazard rates. In first place, LKIS firms are more vulnerable to exit than KIS firms as observed before, thus, this factor can be decisive to remain competitive in the market. Small increments of innovation may have a higher impact for LKIS firms than KIS firms, being KIS firms already associated with higher levels of innovation. For example, the introduction of ICT to the retail sector such as integrated databases or electronic tracking of inventories may turn the supply chain more responsive with reduced lead times and, consequently, improve its overall performance. This is an example of an improvement that is indirectly related to the firm's main activity but may have a strong impact on the firm's performance. Secondly, since KIS firms tend to be more innovative and some are innovation "diffusors" (Miles et al., 1995; OECD, 2006), resorting to a comparison of an average value

may virtually increase/decrease the thresholds used to identify innovators among KIS firms. In other words, innovators LKIS firms are being identified according to lower thresholds (lower means) and innovators KIS firms according to higher thresholds (higher means). On the other hand, this problem is probably mitigated by the high entrance rates from both type of firms. Another possible explanation for the absence of different impact on the LKIS and KIS firm's hazard rate may be related to the importance of innovation in firm survival. Innovation may be a determinant of firm survival so powerful and effective, that equally benefits KIS and LKIS firms.

Hypothesis 6 comprises the role of exports in firm survival. The estimates show that exporters are more likely to survive than non-exporters. According to Bernard et al. (1995), exporters are more productive, profitable and competitive, which rises the survival chances. Also, resorting to exports may help small firms to overcome low performance in domestic markets (Hirsch and Lev, 1971), sometimes caused by unfavourable macroeconomic environment such as the Portuguese financial crisis. From the analysis carried out in Section 3.3.7, there was an increasing trend for exporters, exports volume and average export ratio for both types of firms, which may reinforce the previous argument. Regarding the impact in KIS and LKIS firms (sub-hypothesis 6.1), the same pattern occurs, where LKIS firms benefit more from exporting than KIS firms. International trade for service sectors may require some flexible organizational structure (e.g., ICT). Perhaps this flexibility is less achievable among LKIS firms, however, they benefit the most from the performance boost that exporting may provide (e.g., e-commerce in the retail sector).

Finally, hypothesis 7 shows the influence of improving or not the firm sales per employee (growth rate). Through the marginal estimates, it was possible to show that growth in terms of sales per employee increases the probability of remaining in the market. According to Audretsch (1995), young firms that are able to adjust to the market requirements may experience high growth rates and, consequently, higher prospects of survival. Also, improving the sales per worker can be consequence of the rise in productivity and efficiency, which may improve survival rates (Jovanovic, 1982). The results regarding sub-hypothesis 7.1, i.e., the marginal effects of growth on LKIS and KIS hazards rates, reveal that the impact is higher for LKIS than KIS firms, similar to the remaining factors. Here, there is a higher gap between the margins values, suggesting that LKIS firms that are able improve their productivity and efficiency may boost, in larger scale than KIS firms, the probability of survival. Once again, this result can be justified by the greater impact of gains of efficiency for LKIS firms, due to their higher standardisation and labour-intensive services.

In summary, all the hypotheses concerning the general effect of the determinants were confirmed and aligned with the literature. However, the estimates from the average marginal effect of interactions with the type of industry shows other results from those anticipated. We were expecting a higher and beneficial effect of the different factors on KIS firms hazard rates, since they present lower hazard rates in general. Our expectations was to discover "specific triggers" that lowers the hazard rates from this type of firms. However, the estimates unveiled the opposite scenario. Generally, LKIS firms benefit more than KIS firms from the determinants of firm survival, according to our models. Possibly, this is related with industry specifics features such as more standardized services, labour intensive activities,

innovative services process that are easily imitable, among others (Tether and Hipp, 2002). These traits, along with low entry barriers, may justify indirectly the high number of competitive markets in LKIS firms[11]. Also, KIS firms are characterised for being more innovative, customized and customer-oriented, which may provide them some leverage over LKIS hazard rates. In addition, recent literature points out an increasing demand of KIS firms (OECD, 2006; Muller and Zenker, 2001; Miles, 2005), whereas the market is "flooded" of LKIS firms that may exceed the demand of those services, turning their markets more competitive.

5.2 Research Issues, Limitations and Suggestions for Future Work

5.2.1 Research Issues

This dissertation required an extensive research in several subjects. Some of these were not explored due to either unsatisfactory results or unfeasibility. Hereby, we present some of the failed experiments and hypotheses.

- **Variables Form** - As a first step from our research, we experimented several models with different combinations of variables and interactions. From these experiments, we concluded that most relevant results (statistically significant estimates) were associated to models with the categorical variable of each determinants. Perhaps this is related to the heterogeneous sample, and possible KIS and LKIS inter-industries differences. Nevertheless, we think that these variables represent fairly the firm survival determinants from this study;
- **Failed Hypotheses and Models** - We experimented other variables that did not provide us valuable preliminary results, so, were discarded from the study. More specifically, market concentration as a variable/determinant failed our preliminary tests (through Kaplan-Meier method). We also concluded that return on equity was not a proper variable to characterise firm efficiency. Market share growth also was dropped as a variable due to possible redundancy, i.e., a positive/negative evolution on the market share may be consequence of the firm's action regarding the other variables already present in the models;
- **3 - Way Interactions** - We also experimented possible 3 - way interactions between knowledge-intensity, age and the remaining variables, separately. However, most of the results have proven to be unclear and unsatisfactory. Also, we did not found studies from the literature that could sustain hypotheses related with the 3 - way interaction, so, we decided to withdraw this possibility.

5.2.2 Limitations

We performed the research tasks proposed in the beginning of the thesis, however, there were some limitations that we should highlight for a better understanding of our results. Hence, we present the following limitations:

- **Unexplored Determinants** - Given the extent literature on firm survival, certain factors were not taken into consideration due to limitations regarding the information available by SCIE. This is the case of a founder's education level that, as discussed in Chapter 2, has a great importance in the

first years of activity. Another case was the minimum efficiency level. there is indication from the literature that the number of facilities/establishments could be a head start for a variable to cover that factor. However, there was no information from the number of establishment or the founder's education level. Nevertheless, the set of hypotheses proved to be sufficient to show us an overview of the main factors for KIS and LKIS firm survival;

- **Variables Definition** - Due to the heterogeneous firm sample, it was a challenge to figure it out a proper and general way to classify our firms as innovators and exporters. Finally, we decided to resort to a comparison of the corresponding ratio to an arithmetic mean, minus the standard deviation. This tactic may result for the first few years of duration on the sample, however, it starts to be less effective over the years. As we later on confirmed, innovators (exporters) tend to survive more years than non-innovators (non-exporters). So, as time passes by, the "survivors" will rise the average value, leading to unreliable classification. Even though the entrance of new and innovators/exporters firms may appease this effect, we are not certain of the real effectiveness of this classification on the long term;
- **KIS and LKIS Definition** - Another challenge that we faced was the definition and research of KIS/LKIS firms. Firstly, we found a limited number of reliable studies related with knowledge-intensive, which narrowed the extent of viable views on the subject to support some of the results obtained. Secondly, each study had either a different definition of KIS or it was more focused in a subset of KIS firms, namely KIBS firms. To facilitate our study, we utilise the information available by SCIE data-set (CAE Rev.3 code), that classifies KIS and LKIS sectors according to technology proximity and proportion of educated workforce (33.33%), which narrows our study. Also, even though our main purpose was to study knowledge-intensity in the service sector, having an additional group of manufacturing knowledge-based firms to the study could add some interesting insights regarding the value of knowledge in firm survival;
- **Unobserved Heterogeneity** - While conducting our models, it is assumed that all the differences that we observe between firms are captured by our explanatory variables (vector X). However, there are unobserved individual effects, usually referred as "frailty", that may produce bias effects on our results if these variables are relevant such as, for example, omitted variables (unobserved or intrinsically unobservable) and/or measurement errors in observed survival times or regressor (Jenkins, 2005). For instance, the education level of the owner and employees, previous experience in the specific market and/or quality of management could be important variables to our study, however, were not included to our models due to limited data available. In survival models, usually, ignoring frailty may overestimate the degree of negative duration dependence in the baseline hazard (Lancaster, 1990). A possible solution to this problem is to assume the existence of this frailty and include it in our model, by specifying the distribution of this random effect (Cleves et al., 2008). This detail was not cover on our study, however, we are aware of its effect while interpreting the results of our models.

5.2.3 Suggestions for Future Work

As a suggestion for future work on this subject, a more extensive research within the several sectors of each group and subgroups of KIS and LKIS firms could give us more clues regarding the factors that may trigger differences between KIS and LKIS firms hazard of exit. As a guess, high-tech firm may seem like a good point of start, since this type of firms typically is associated to the constant introduction of innovation into the market. Yet, these firms are more vulnerable to possible takeovers and higher competitiveness, which could turn into a setback. Nonetheless, being able to study more deeply the diverse type of firms in each subgroup could aid a better interpretation of the main results. We also suggest taking into account frailty in further models, since it could improve the consistency and adequacy of the results. Another possible change in the methodology could be resorting to discrete models instead of continuous models. Since the time span of our study fits the requirements of this type of survival analysis models, the results from discrete models could be more adequate and reliable to this study.

Chapter 6

Conclusion

This dissertation main goal is to determine the possible factors of firm dynamics in knowledge-intensive and less knowledge-intensive industry. Through an extensive research of the current literature and characterisation of the sample, it was possible to advance hypotheses in order to explain the behaviour of exits in the service industry, with a special focus on the role of knowledge-intensity on firm survival. To achieve that, we apply the piecewise-constant exponential semi-parametric method. Additionally, we discuss some of the main limitations of our study and suggestions for further research on the subject.

From the literature review, we find that age, firm size and start-up size (in terms of number of employees) are irrefutable factors, with several studies highlighting its relevance. We also find that innovation and exports are important determinants of survival, since innovation is a key factor for survival to firms that rely on knowledge-intensity. Moreover, the relevance of exports has been growing in the Portuguese economy, especially after the economic recession where several firms had to expand their business abroad to survive. We also consider growth rate to cover a component of internal productivity and efficiency. Finally, we also analyse the firm's typology regarding knowledge-intensity (KIS or LKIS) impact, and interaction with the other factors. From this research, we choose a set of hypotheses related with the following variables: type of industry (KIS or LKIS), age, size, start-up size, innovation, exports and growth rate. Also, we cover some sub-hypotheses regarding the knowledge-intensity typology and remaining firm survival determinants. Through the average marginal effects of our semi-parametric duration model, we find that:

- KIS firms have lower hazard of exit than LKIS firms, due to a higher proportion of educated workers, increasing demand for KIA activities and further role as innovation carrier;
- Older service firms have lower hazard of exit, due to gains in know-how and experience in the market. However, there is a possible interference of unobserved heterogeneity, that could disturb our results. LKIS firms benefit more from ageing than KIS firms, due to the superior gains in efficiency of standardised and labour-intensive services that LKIS firms usually provide;
- Large service firms have lower hazard of exit, leveraged by less financial constraints and more stability. Also, LKIS firms benefit more from larger size than KIS firms, since LKIS firms are more labour intensive and benefit more of economies of scale, whereas KIS firms usually remain small

for efficiency purposes;

- Entering the market in large scale lowers the hazard of exit, since it leads to higher prospects of success. LKIS firms benefits more from this determinant than KIS firms, since it is more labour intensive and larger scale can turn into an competitive advantage. KIS firms are more capital intensive labour, which entering with a large size can lead to unnecessary higher costs;
- Innovators have lower hazard of exit than non-innovators, since investing in innovation can be a tool to overcome other disadvantages (e.g., size, competitive market), and lead to higher growth rate sales. Here, LKIS firms benefit more from this factor than KIS firms, probably due to LKIS firms higher vulnerability to closure and competitive markets, and KIS firms tendency to be innovator and create innovation;
- Exporters have lower hazard of exit than non-exporters, since exporters are more productive, profitable and competitive. Also, exports is an excellent tool to overcome low performances in local markets. Once more, LKIS firms benefits more from being exporter than KIS firms, due to the superior performance boost that exporting provides to LKIS firms, protecting them from closure;
- Growing firms, in terms of sales per employee, have lower hazard of exit than not growing firms, since they are more productive and efficient. LKIS firms are more influenced by this factor than KIS firms, due to the beneficial effect of gains in efficiency for LKIS firms.

The main results are aligned with findings of the literature review. There is no doubt of the importance of each determinant of firm survival studied for the service industry. It is possible that our results may have been influenced by frailty, probably caused by omitted variables (e.g., founder's education level, quality of management). Also, due to lack of indications from the literature, we had to chose the baseline hazard function, which could influence negatively the results obtained. Despite that, we believe that this set of variables gave us a glance of what factors should service firms invest, in order to survive in this competitive economy. As the knowledge-based economy continues to rapidly evolved, companies must be aware of the new trends in the market and build cope mechanism to surpass possible adversities from the external environment. It is often said that firms that survived periods of economical retrenchment (e.g., Portuguese crisis) become more resilient to unfavourable events. However, this is not enough. Being responsive to market needs, explore new markets, introducing/acquiring innovation products to/from the market, are few generic examples of strategies that firms may utilise in order to overcome difficulties without shutting down their activities.

Regarding the effect of these determinants by knowledge-intensity, there is a persistent pattern that all factors have higher influence on LKIS firms hazard. Part of the explanation lies on the generic traits of these firms such as more standardised services and/or easily imitable service processes. This may lead to low barriers of entry, increasing entry rates and further competitiveness among LKIS markets. On the other hand, KIS firms activities are usually more customised and client-oriented, turning the service provided more specialised and unique, consequently, improving their survival. However, the service industry is considerably diverse, and do not always fit entirely in these two profiles. So, instead, we may suggest that the degree of customization of the service output and proportion of educated and skilled workers may dictate the extent of exposure to closure for service firms.

We executed our research tasks with some useful insights and contributions to the KIS and LKIS industry literature. Our suggestion for future investigation is to resort to alternative survival analysis models, such as discrete models, to ensure more robust results, and to perform a more detail analysis into the subgroups of KIS and LKIS, to uncover other possible conclusions.

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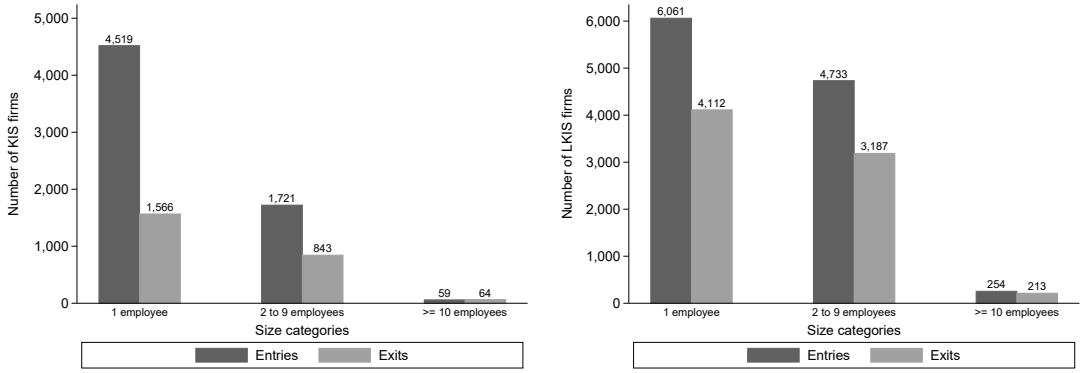
Appendix A

A.1 Data Description



(a) KIS **(b)** LKIS

Figure A.1: Entries and exits of firms by knowledge-intensity and size category (2011).

A.2 Other Estimates

Table A.1: Average marginal effects with interactions (whole sample).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
KIS	-0.027***	-0.027***	-0.026***	-0.026***	-0.027***	-0.027***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Age:						
3 to 4 years	-0.290***	-0.287***	-0.030***	-0.031***	-0.014***	-0.014***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
5 to 6 years	-0.051***	-0.051***	-0.052***	-0.052***	-0.031***	-0.032***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
$\geq$ 7 years	-0.063***	-0.063***	-0.064***	-0.065***	-0.053***	-0.054***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0009)	(0.0010)
Start-up size:						
2 to 9 employees	0.032***			-0.004***		
	(0.0012)			(0.0008)		
$\geq$ 10 employees	0.072***			-0.009***		
	(0.0077)			(0.0028)		
Log of start-up size		0.033***	-0.004***			
		(0.0009)	(0.0006)			
Size:						
2 to 9 employees	-0.054***					-0.033***
	(0.0011)					(0.0007)
$\geq$ 10 employees	-0.074***					-0.045***
	(0.0018)					(0.0014)
Log of size		-0.050***			-0.026***	
		(0.0010)			(0.0005)	
Innovator	-0.044***	-0.042***	-0.052***	-0.052***	-0.040***	-0.041***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0006)
Exporter	-0.030***	-0.029***	-0.033***	-0.033***	-0.031***	-0.031***
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Growing	-0.105***	-0.107***	-0.099***	-0.099***	-0.082***	-0.082***
	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0008)	(0.0008)
Number of observations	460,242	460,242	460,242	460,242	632,893	632,893
Number of firms	142,534	142,534	142,534	142,534	198,859	198,859
Log likelihood	-71,838	-71,538	-73,181	-73,207	-99,841	-99,960
p-value of the log likelihood test	0.000	0.000	0.000	0.000	0.000	0.000

Note: Standard errors in parentheses. All models control for sector, region, unemployment rate and GDP per capita. For categorical variables, base levels are not presented (age = 1 to 2 years; start-up size = 1 employee; size = 1 employee; non-innovator; non-exporter; not growing). *Significant at 10%, ** Significant at 5%, *** Significant at 1%.