Entry, Spin-offs and the survival of new ventures: evidence from the Swiss ICT industry

Supervisor:
Prof. Valentina Tartari

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Davide Sangiuliano

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Abstract

Relying on a dataset of 259 start-ups established between 2000 and 2013 in the Swiss ICT industry, this thesis aims to examine and compare the survival performance of start-ups controlling for the pre-entry experience of the founders. Results suggest that spin-offs, in particular demand spin-offs, and university start-ups survive longer than inexperienced firms. In addition, consistent with previous literature, we found that teams composed by multiple founders tend to perform better than single founder start-ups. Moreover, our findings suggest that start-ups with founders belonging to different backgrounds are more likely to file patents than all other types of entrants. Interesting insights concerning venture capital funding and founders educational background are also presented.
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1. Introduction

Entry plays a fundamental role in all industries and recent works suggest that pre-entry experiences of founders are quite different among new firms, affecting their performance (Carroll et al. 1996; Klepper and Simons, 2000; Thompson, 2004; Geroski et al., 2002). New firms are based on knowledge and experiences that depend on the human capital their founders accumulated during previous employments. Research in entrepreneurial dynamics, in particular in high technology industries, has stressed the role of educational level, professional background, and other characteristics related to the founders of start-ups.

Most of the studies have explored the performance of new ventures based on their founders’ pre-entry working experience, indentifying different categories. Spin-offs, which are companies founded by former employees of incumbent firms, are usually found to perform better than other entrants in high-tech sectors (Klepper and Spleeper, 2005). Demand spin-offs, which are entrants coming from user-industries, have generally showed superior performance in industries with high demand heterogeneity in terms of user groups and applications (Fontana and Malerba, 2010). Lastly, university start-ups, which lack industry experience but have high technological know-how, are known to outperform in knowledge intensive sectors such as biotechnology, pharmaceutical and information technology (Zhang, 2008).

Other scholars focused on human capital differences such as educational background of founders or heterogeneity of the founding team (Roberts, 1991; Agarwal et al., 2004).

Finally, parallel literature has evaluated other characteristics related to the company such as, venture capital support, geographical location, and the degree of innovativeness (Porter, 1990; Baptista, 2000; Klepper, 2007; Cefis and Marsili, 2006; Fontana and Nesta, 2009; Hellmann and Puri, 2000).

This study aims to take a step forward by examining the relevant characteristics that affect survival rates and innovation in the Swiss Information and Communication Technologies industry. This sector is an appropriate setting for our analysis because is characterized by fast technological changes and high knowledge spillovers (Agarwal et al., 2008).
A dataset of 259 start-ups founded between 2000 and 2013 in the Swiss ICT industry has been created, and different firm categories, based on founders pre-entry experience, have been considered.

After performing a survival analysis using both continuous and discrete time specification models, we showed that experienced start-ups have better performance that inexperienced firms. Spin-offs, in particular demand spin-offs, enjoy a lower hazard rate than other entrants, confirming previous findings in high-tech industries (Adams, Fontana, and Malerba, 2013). Moreover, firms founded by a team perform better in terms of survival than those founded by a single founder.

In addition, using patents as a proxy for innovative activity, we found that firms founded by entrepreneurs with mixed working experiences are more innovative than others. Finally, venture capital support and related educational background play a fundamental role, increasing the probability of filing patents.

This thesis is organized as follows: in section 2 the main findings of academic research on spin-offs, human capital, and survival of new firms are examined. In section 3, the ICT industry and its major characteristics with a focus on Switzerland are discussed. Section 4 includes the description of the dataset used in the analysis, the descriptive analysis, and the econometric models selected to enrich the results. In section 5, preliminary results, robustness check, and further insights are provided. Finally, section 6 presents conclusions and limitations of the study.
2. Literature Review

In recent years the phenomenon of entrepreneurship has been studied by many authors, in particular in high technology sectors. This interest has been caused by the incredible growth of new firms in industries like semiconductors, lasers, disk drives, biotechnology and information technology.

Numerous analysis have focused on pre-entry experience of founders and how this knowledge affects the survival period of new ventures. Literature that studied new entrants in many industries, in particular in high-technology, found that the characteristics of founding teams affect both the choice to enter an industry and the ability of new firms to survive in the long period (Gimeno et al., 1997; Mitchell, 1989; Sleeper, 1998; Carroll et al., 1996; Klepper and Simons, 2000; Klepper, 2002; Agarwal et al., 2004; Bruderl, et al., 1992; Khessina and Carroll, 2008; Chatterji, 2009; Dencker et al., 2009).

Usually, survival rates of spin-offs (independent companies whose founders were previously working in incumbent firms in the same industry) have been analyzed compared to inexperienced entrants (start-ups whose founders came from universities, research organizations or completely unrelated industries). In this work we tried to categorize the new ventures according to their different types of knowledge and try to identify which factors are determinants for the success of a new firms. To simplify the understanding of our classification scheme we distinguish between four types of knowledge (Adams, Fontana, and Malerba 2013): technological, market, application, and organizational knowledge. Technological knowledge reflects the information regarding innovations or technical developments in terms of products, technologies or processes, and the ability to use it to generate new innovations. Market knowledge, on the other hand, reflects the information regarding market opportunities and the ability to commercialize new products that meet customers’ needs faster than competitors.

Application knowledge, instead, requires deep knowledge of the downstream sectors of the firm and the capability to solve user’s problems. Finally, organizational knowledge involves unique sets of resources and capabilities that affect the strategies, products, and processes used to compete in the market (Cyert, Kumar,
and Williams, 1993; Cohen and Levinthal, 1994). This last characteristic does not belong to a single individual but should be part of the founding team.

With the clear awareness of these different skills and capabilities incorporated in any new company, in the following sections we will review the main theoretical findings of last years based on our categories of start-ups. First, literature on spin-offs will be reviewed, distinguishing between classical spin-offs from the same industry and user-industry spin-offs. Then, findings on university start-ups and inexperienced start-ups are taken into consideration. Finally, some additional considerations on other determinant factors that have been found to affect firm survival will be reported.

### 2.1. Spin-Offs and Demand Spin-Offs

Over the years a number of theories have been developed to explain spin-offs’ formation and reasons for success. According to Klepper (2001), four different theoretical perspectives are classified. The first perspective is based on agency theories: the employee of an incumbent firm makes a path-breaking innovation and is not able to contract with the employer, leading to spin-offs (Wiggins, 1995). The length of time it takes to develop the discovery, the low probability of success and the high capital needed to develop it, are key determinants of the opening-up of new sub-markets.

The second perspective is linked to organizational capability theories. Typical of architectural innovations and competence-destroying innovations, these theories explain spin-offs as a consequence of organizational limitations of incumbents’ firms. The reason is that high structured organizations are not able to implement some innovations, creating opportunities for the formation of spin-offs (Tushman and Anderson, 1986; Bhide, 2001; Christensen, 1993; Henderson and Clark, 1990).

The third perspective, is that spin-offs are considered as the result of employee learning. One of the most cited employee learning theory states that the better a firm’s knowledge, the lower the wage R&D workers are willing to accept, because the prospect of establishing their own firm increases (Franco and Filson, 2000).
model suggests also that the higher the knowledge of firms the higher the probability of spawning spin-offs.

The last perspective, generally called theory of the heritage of spinoffs, compares the process of creation of a new venture from an existing firm to the relationship between parents and their children. Dyck (1997) on this topic conceptualized spinoffs as children and the previous company as parents, suggesting that sometimes parent companies are supportive towards their spin-offs.

Those and other theories are helpful in order to understand the reasons of the creation of new ventures and the outstanding performance of all types of spin-offs.

As mentioned above, spin-offs are independent companies founded by people that were previously working in the same industry. In some cases spin-offs are sponsored by their parent firm, but in general they do not maintain any link with their prior employers (Klepper and Thompson, 2005). In this section, we want to focus only on spin-offs which founders come from parent companies that were active in the same industry of the new venture, in order to better distinguish it from demand spin-offs. Usually these kind of spin-offs are founded because the employees of the incumbent firm leave their company after becoming frustrated with their previous employers (Garvin, 1983). Their frustration could be driven by the discovery of an innovation that is rejected by the old employer. The opinions about the contribution of spin-offs to economic growth differ among authors. Garvin (1983), Klepper (2001) and Agarwal et al. (2004) among others, have pointed out that knowledge and routines that founders accumulate during their professional and educational experience are often transferred and used into their new companies, and this affects the survival and performance of de novo entrants.

Some say that spin-offs are a source of innovation, because they compensate for the inertia of their parents (Klepper, 2002). Others perceive spin-offs as parasites, that leverage on the effort of the incumbents, that in turn lose their incentives to innovate (Jackson, 1998).

Founders of these kinds of spin-offs, as a result, have both technological and market knowledge (Adams, Fontana, and Malerba, 2012). On the other hand, they
are less likely to have knowledge of the field in which their products or services are used (application knowledge).

There are different studies that have focused extensively on spin-offs’ performance, in order to understand if they have advantages over other ventures to enter an industry and the effect on their ability to survive. The results of most of these studies on specific industries are that spin-offs, in general, perform better than other entrants (including firms with founders coming from either university or inexperienced firms), and they also show a lower hazard ratio compared to the others.

Klepper (2002) developed a database to identify all the entrants into the U.S. automobile industry between 1895 and 1966. He gave a first classification of new ventures into four categories, according to their backgrounds. Firms that diversified into automobile from other industries, de novo firms with founders that were working in other industries, de novo firms with founders that were working for an automobile company (spin-offs), and a residual category for all the other firms. He found that diversifying firms, on average, perform better than the other three categories of de novo firms. In addition, and more interesting for the purpose of this study, entrants founded by people working for automobile industry dominate the industry, performing better than diversifying firms. A possible explanation given by the author is that experienced founders tend to keep in contact with their previous employer, taking advantage of the experienced firms.

Further evidences come from Helfat and Lieberman (2002), that predicted a relationship between historical antecedents of founders and the probability to enter a market and outperform. In particular, they found that the greater the similarity between the capabilities required in the industry and the pre-entry capabilities, the higher the probability that a firm will enter the market. Moreover, the extent of similarity affects the survival period and long-term performance of the firm.

The analysis of the disk drive industry done by Agarwal et al. (2004), provides supporting evidence of the links between human capital, knowledge capabilities, and spin-offs formation. They collected information over the period 1977-1997, focusing on the above mentioned technological and market knowledge of incumbents and spin-offs in the fast changing industry of disk drive. Results showed that incumbent firms, with strong technological know-how and market knowledge, generate less
spin-offs than firms with only one of these capabilities. Moreover, the incumbent’s
know-how at the time of foundation of a spin-off contribute to the spin-off's
capabilities and increase the probability of survival of the new ventures.

Spin-offs are found to be very high performing companies also in the U.S. iron
and steel shipbuilding industry between 1825 and 1914 (Thompson, 2005). Pre-
entry experience closely related to their new venture is found to positively affect their
survival rate, and this effect is extremely persistent, even if we control for firm size.

In the laser industry, Klepper and Spleeper (2005) suggested that spin-offs
initially target niches that overlap with their parent’s markets, but finally they move to
different markets. Spin-offs are most concentrated among more established firms
and acquisitions of firms increase the chances of spin-offs, because management is
probably not perceiving the opportunities generated by the firm. In general, spin-offs
in the dataset perform better than start-ups and similar to diversifying entrants from
near industries. It was also found that firms located around Silicon Valley have higher
spin-off rates, due to their ability to create knowledge spillovers. Finally, spin-offs are
inheriting products and markets from their parents, but as in human relationship, they
gradually differentiate from them.

In 2005, Klepper and Thompson developed a new model of spin-offs formation
driven by disagreements with their parent firms. They reviewed previous existing
theories of spin-offs generation in many high-tech industries and predicted that the
hazard rate of spin-offs increases initially with the age of the parent firm, and then
decreases to zero. Also, spin-offs are found to be more likely in industries where the
target is less clear, consistently with the huge number of spin-offs in high-tech
industries (Garvin, 1983). Finally, the model predicted that spin-offs have lower
quality than their parents and that they are more likely to happen when decision-
making is managed by a strong hierarchical structure.

It has also been shown that spin-offs survive longer than other start-ups in the
U.S. rigid disk drive industry (Franco and Filson, 2006). Following the previous
analysis of Christensen (1993), they found that the probability to generate spin-offs
and survive is strongly related to the firms know-how and unrelated to firms’ size. In
addition, employees’ mobility is an other important valuable factor that should not be
prevented, because it is one of the main causes of spin-offs creation. As a
consequence, technological diffusion in knowledge-intensive industries is an important factor and public policies are key to effect employees mobility. On the opposite side, preventing mobility would have a negative effect on social welfare.

In 2007, Buenstorf went beyond the prior research done by Klepper and Sleeper (2005) on the U.S. laser industry, focusing on 40 years of evolution of the German laser industry and making a distinction between types of entrants, including different spin-offs categories. Overall, the results suggested that spin-offs from existing laser firms have higher survival period than both university startups and inexperienced firms. In particular, the process of learning of the employees in incumbent firms benefits subsequent spin-off founders in terms of longevity of the company. In addition, technological capabilities are showed to be less important than market knowledge for the success of firms in the German laser industry.

Similar results were obtained by Chatterij (2007) on the medical device industry, looking at the impact of pre-entry experience on the performance and innovation of the startups. After the study he found that spin-offs obtain funding more quickly and receive higher valuations, compared to other entrants. Moreover, there was little evidence that technical knowledge acquired by spin-offs at the parent firm is the most important driver of their superior performances, compared with other firms in the medical device industry.

During the same period, Bayus and Agarwal (2007) gave a further contribution to the study of the relationship between pre-entry experience and firm’s success, examining also what firms do after they enter. The empirical setting for the analysis was the U.S. personal computer industry in the 1974-1994 period. According to their results, diversifying entrants have an initial advantage over startups, because they are better able to focus on the product standard once it is known. Typical industry cases of successful spin-offs, such as Compaq and Gateway, confirm this theory. However, they found the reverse for later entrants. Once the product standard is established, survival depends on introducing products very innovative, and entrepreneurial startups tend to care less about cannibalizing their products. As a result, startups entering later in the industry outperform diversifying entrants in terms of survival period. Apple and Dell are two examples of startups with no pre-entry experience linked with firm affiliation that performed very well.
Although these different studies suggested that corporate spin-offs constitute an important part of new entrants and they usually perform better than other entrants, they are not the only type of firm that we want to investigate on this thesis. We propose that there is at least one further category of de novo entrants, whose founders come from downstream industries, that means industries that are clients or users of a specific product or service. Actually, there are two ways of entry from demand side: start-ups coming from demand and vertical integration by large users. Knowledge about uses and applications becomes a key asset for the new firms and usually this has a positive effect on survival period. A second advantage of user spin-offs is that fixed costs and capital equipment costs tend to be lower than other categories of start-ups and this makes easier for a small company to enter the industry. In general, heterogeneity of demand increases opportunities for demand spin-offs (Fontana and Malerba, 2010).

Looking again at the four knowledge categories introduced previously (Adams, Fontana, and Malerba 2013), we can understand that demand spin-offs are less likely to have technological knowledge that is typical of the industry. On the other hand, they will show an extensive market knowledge, sometimes within a defined niche of users or sub-market that they want to exploit. Of course, they are also more likely to have a better application knowledge compared to classical spin-offs, because of their experience with products or services coming from previous employment.

Many authors in the past have examined the phenomenon of entry from demand side, beginning with Lane (1989), Mitchell (1989), Klepper and Simons (2000). They found that people with experience in industries related with their new start-ups are more likely to enter and outperform other types of entrants.

In particular, Lane (1989) and Mitchell (1989) found that firms with pre-entry experience in related products are more likely to enter, respectively in the Automated Teller Machine (ATM) industry and in new diagnostic imaging markets, although they are not among the earliest entrants.

In the U.S. television industry, Klepper and Simons (2000) collected information of all the producers to analyze how radio experience influenced entry and
performance of the television industry. The results were all confirming their hypothesis: firms coming from the radio industry are more likely to enter television manufacturing industry, have higher innovation rates, greater market shares, and survive longer than all other entrants.

Fontana and Malerba (2010), identified other examples of de novo entrants from the downstream industries. They collected information on more than one thousand firms in the semiconductor industry between 1997 and 2007, in order to understand the relationship between firm background and survival. Consistently with the existing literature in high-tech industries, classical spin-offs have a lower hazard rate compared to inexperienced firms. What they found, in addition, is that firms with background experience in application sectors of semiconductors (demand spin-offs), enjoy a lower hazard rate compared not only to inexperienced firms, but also to classical spin-offs. As we explained above, indeed, firms coming from demand side have better knowledge about applications and markets, and this constitutes a competitive advantage with respect to all the other types of firms. Moreover, heterogeneous group of founders and educational level seem to be important to reduce the risk of failure.

A further study on semiconductor industry conducted by Adams, Fontana, and Malerba (2012) took a step forward. After creating different categories of new start-ups based on their pre-entry experience, they understood the link within different product categories and survival rates. Results indicated that spin-offs are more likely to enter only standardized product categories, while demand spin-offs focus on both standardized and customized product categories. In addition, spin-offs have lower hazard rate than other entrants in standardized product categories, while demand spin-offs have lower hazard rate in customized products categories. Consequently, other types of entrants (e.g. university spin-offs and inexperienced start-ups) are less likely to enter and survive in both product categories.

Previous findings indicated that demand spin-offs have to be considered a different category from other de novo entrants, such as corporate spin-offs. At the same time they don’t have to be associated with start-ups coming from completely unrelated industries or universities and research environment.
2.2. University Start-ups and Inexperienced Start-ups

There are at least other two main categories of entrants that should be considered in our analysis. University spin-offs are usually new companies which founders are coming from research institutions such as universities or other laboratories. The reason why they decide to leave their institution to found a new venture is because they want to commercialize the technologies and exploit the intellectual properties they had discovered within the research labs. In particular, in high-tech industries such as ICT, university spin-offs are responsible for the generation of leading technologies and are a considerable part of total start-ups (Shane, 2004).

The Information and Communication Technologies industry provides many examples of academic start-ups that outperformed during last years. The founder of many successful ventures Jim Clark (e.g. Silicon Graphic, Netscape, Healtheon, myCFO and Shutterfly.com), was a professor at Stanford University and University of Santa Cruz. Companies like Cisco Systems, Lycos (internet search engine), and Akamai (internet content delivery network) are other famous examples of university spin-offs in the ICT industry.

Compared to corporate and demand spin-offs, university start-ups in general have technology knowledge linked with their scientific background, but usually they don't have market, application and organizational knowledge. In fact, they lack experience in the industry and are not aware of the needs of users. Finally, they don't easily find links to other industry players (e.g. customers, suppliers, competitors) and this is critical for commercial success (Vohora, et al., 2004).

Many studies focused on the interaction between business sector and scientific institutions through knowledge and technology transfer, and the performance of university spin-offs.

Shane and Stuart (2002) focused on 134 new companies founded to exploit MIT-assigned inventions between 1980 and 1996. They tried to understand why some university spin-offs are more successful than others. Results showed that firms with founders linked to venture capitalists are less likely to fail, and technology licensing
offices across universities are an important vehicle of knowledge transfer and an important driver for economic activity.

In the study of Arvanitis, Kubli and Woerter (2008), the factors determining the propensity of spawning spin-offs from university are investigated. They collected data on Swiss research institutes and found that institutes with a stronger orientation to applied research and lower teaching obligations are more likely to be involved in knowledge and technology transfer activities. In the second part of the research, they found that the focus of research institutes (basic research or applied research) does not influence the propensity for patenting and the formation of spin-offs. Nonetheless, high teaching obligations are negatively related with licensing and spin-offs creation.

In relation to performance of this category of start-ups, Zhang (2008) examined a U.S. venture capital database of university spin-offs. What is relevant to our study, is that he found that university spin-offs have a higher survival rate compared to other entrants, even if there is no significant difference in the amount of money raised from venture capital.

When it comes to the reason why these kind of spin-offs perform better than competitors, we can identify three main possibilities. First, opportunity costs for universities’ employees are higher than other founders, and this leads to better screen the ideas before they create a new company. Second, there are some advanced technologies developed in the research environment that are very difficult to imitate, and this is a clear competitive advantage for university spin-offs. Third, incubatory services are often used in research institutions in order to support entrepreneurial activities and are financed also by governments. This may help university spin-offs to start a new venture and increase the chances to survive.

When we compare classical spin-offs and demand spin-offs to the other new ventures we need to consider also a further category: inexperienced start-ups. There is a clear distinction between this kind of venture and university spin-offs. The former are totally lacking pre-entry experience in the field of the new start-up, while the latter possess at least technological capabilities in the industry.

As a consequence, we can consider inexperienced start-ups both firms with founders coming from different industries (e.g. finance, consulting, or law), and
founders with no experience at all. That means, they are lacking all the four types of knowledge take into consideration (Adams, Fontana and Malerba, 2012). They have neither the knowledge of the incumbent industry nor the one of the market sector, nor the application knowledge and organizational know-how.

Inexperienced start-ups are frequently concentrated among the early entrants to a market (Helfat and Lieberman, 2002). In fact, in the initial stage of a new market there is great uncertainty about the capabilities required and customer needs. Limited economies of scale, due to the modest demand, lead to low cost of entry. This is the right environment for the expansion of entrepreneurial start-ups without fundamental knowledge.

According to the theory, this category of start-ups performs worse than the others, with lower survival period and high rate of failure. Dencker et al. (2009) examined these patterns using a survey of firms founded in the region of Munich across multiple industries, in order to understand if pre-entry capabilities enhance post-entry performance or not. In particular, they studied if founders’ management and technical experience influences the effectiveness of early-stage business planning and product-line change. Findings suggested that pre-entry knowledge increases significantly the likelihood of firm survival. Founders with low levels of pre-entry knowledge and management experience are twice as likely to fail as those with high levels of both pre-entry and management experience. Nonetheless, learning activities are not always beneficial: early-stage business planning decreases firm survival, while product line change is associated with increasing firm survival.

2.3. Other Determinants of Start-Ups Survival

Former variables capturing the background of the firms are important to make a clear distinction between start-ups with and without pre-entry knowledge of the specific industry. However, there are other characteristics that belong to the founding team or the new venture in general that make the difference in terms of success. Many authors have stressed the concept that the quality of the experience that new firms endowed is as important as the possession of any pre-entry experience (Agarwal et al., 2004; Klepper, 2007). That means, the probability of survival for firms
with high relevant experience is higher that those firms who have less relevant experience. Thus, variables that indicate the type of start-ups based on pre-entry experience are not sufficient when investigating factors affecting survival and performance of new ventures. Indeed, it is interesting to include in the analysis also a list of control variables for the educational background of the founders, the different composition of the founding team and other intrinsic characteristic of the start-ups (e.g. geographical location, venture capital support or innovativeness).

2.3.1. Number of Founders

According to the literature, firms with multiple founders have generally a lower hazard rate than firms with single founder, since they can share more skills and capabilities (Cooper and Bruno, 1977; Roberts, 1991). Cooper and Bruno (1977) examined the development of new high-tech firms between 1969 and 1976, and the key factors of success of these ventures. In addition, it was found that high growth firms were more likely to be founded by groups of individuals who came from large companies and whose new firms entered similar markets with similar technologies.

Roberts (1991) explored the same factors among spin-offs and found that larger founding teams are not characterized by more technical experience, but they have better marketing and administrative skills than small founding teams. His findings showed that this focus on experiences different from specific technologies improves their performance. The implication of these results is that the more diverse the experiences of the founders, the better the performance of the start-ups.

2.3.2. Mixed Background

Furthermore, some other authors have found that team of founders with different industries background improves the performance of the start-ups, because they can leverage different ideas and perspectives combining them in a different way. In the study of Agarwal et al. (2004) on the disk drive industry between 1977 and 1997, they suggested that spin-offs founded by mixed teams (at least one founder
with technical knowledge and one with managerial experience), survive longer compared with founding teams without mixed background.

Pena (2003) also has stressed the positive role of the managerial experience of the founders. The purpose of his study was to analyze the relationship between intellectual capital and new firms survival. Results suggested that education, business experience, level of motivation, organizational capabilities, and business networks are intangible assets that affect positively the performance of new ventures. In particular in the software sector, developers with managerial experience are more likely to found successful start-ups.

On the other hand, founding teams whose members have similar educational background, working experience, or even come from the same company, are more likely to understand each other, considering that they share the same knowledge.

2.3.3. Serial Entrepreneurship

An additional critical determinant related to the founding team seems to be the previous entrepreneurial experience. Gimeno et al. (1997) developed a model to explain why some firms with the same economic performance survive longer than others. Linking the organizational survival to human capital factors and not economic performance, they found that firms founded by serial entrepreneurs survive relatively more than those with no entrepreneurial experience at all.

Haynes (2003) also stressed the role of serial entrepreneurship, considering it a critical factor in predicting venture success. By examining different types of experiences, he determined that entrepreneurial experience is positively related to the firm's outcome.

Nonetheless, some studies pointed out that relevant entrepreneurial background could be a cause of failure (Ucbasaran et al., 2003; Simon et al., 2000). Serial entrepreneurs which retain ownership of several private businesses, sometimes at the same time, may be less motivated than other founders and over confident about their abilities. Eventually, this leads to put less effort in the companies they manage and increases the probability of failure.
Moreover, previous findings have shown the positive role of education for founders (Roberts, 1991; Van de Ven et al., 1984).

In the U.S. courseware industry (software for educational purposes), Van de Ven et al. (1984) collected interviews from company principals on factors influencing the success of start-ups during 1983. Results showed that the educational level of the entrepreneurs is positively related to the company performance. At the same time, pre-entry experience seems to be unrelated to the success of new entrants in the educational software industry.

Roberts (1991) a few years after, conducted research over twenty-five years on several high-tech firms in the area of Boston. In his book, he traced the founding and evolution of these firms, many of which have had technological links with MIT, in order to understand reasons of failures and successes. For what concerns educational background, the majority of the entrepreneurs have a medium level of education (Bachelor or Master degree). Most importantly, in knowledge intense industries, doctoral studies are found to be determinant to give a competitive advantage over the other firms.

2.3.4. Venture Capital Support

During recent years, another important determinant of new firms’ efficiency is the access to financial support, monitoring and training. In particular, venture capital (VC) firms are investing a lot of money in innovative companies with potential for high returns. Since they screen their investments very carefully, they tend to reduce the risk of failure for VC backed firms (Manigart et al., 2002). Entrepreneurs do not only benefit of funding from the venture capital, but they also receive other services such as mentoring, monitoring, professionalization of the company, and recruitment of senior management (Hellmann and Puri, 2000). These complementary services are critical to increase the probability of survival of new firms as they improve entrepreneurs’ knowledge and skills.
2.3.5. Innovativeness and Patenting

Kortum and Lerner (2000) examined the influence of venture capital on patented inventions in the U.S. across twenty industries. They found that venture backed firms are more innovative than other firms, producing more patents and more valuable, if we look at the forward citations.

Using a database of high-tech companies in the Silicon Valley, Hellmann and Puri (2000) found a relationship between venture capital financing and product market strategies of start-ups. Among the new ventures they distinguished innovators and imitators. Innovators are those firms that are the first introducing a new product or service for which no substitute is already offered in the market. Imitators are those firms that are also introducing relatively new products or services, but they are not first movers in the market, and tend to compete on different aspects compared to innovators. Results showed that innovator firms are more likely to obtain venture capital support than imitators. Moreover, VC support is associated with reduction in time to market.

Exploring the possible factors affecting survival and performance of new ventures, many authors have focused on the positive role of innovation (Cockburn and Wagner, 2007; Cefis and Marsili, 2006; Malerba and Orsenigo, 1999; Fontana and Nesta, 2009). Search for creative solutions is one of the essential characteristics of entrepreneurship, and creative individuals are generally more likely to emerge in the market, with no distinction among industries. In particular, high-tech industries, where innovative activity is very fast and fundamental to survive, innovativeness is as important as pre-entry experience. We can see innovation both as an input and as an output. Typical inputs of the innovative activity are research and development, while new products, services or patents granting are typical examples of innovative outputs.

Malerba and Orsenigo (1999) provided evidence of a relation between entry, survival, and patents granting. They based their study on patent data across different sectors in six countries over the period 1978-1991. Findings showed that most of the entrants are occasional innovators that exit very quickly from the market, whereas persistent innovators constitute a small part in terms of number of firms, but a large
part in terms of patents granted. They also found that persistent innovators are more likely to survive than occasional innovators.

In the study of Cefis and Marsili (2004) they analyzed the determinants of firms’ survival probability combining firm level and industry level features in different technological environments in the Netherlands. They compared the difference in survival between innovative and non-innovative firms (innovation premium) in high-tech and low-tech industries. According to their findings, the highest innovation premium belongs to firms active in a high-tech sector. Also, in low-tech industries entrepreneurial firms that innovate have significantly higher probability to survive than non-innovative firms.

The relationship between product innovation and firm survival has also been investigated by Fontana and Nesta (2009), in the high-tech industry. They found that firms located near the technological frontier are more likely to survive. On the other hand, if they are not able to survive as free-standing enterprises they will probably be acquired, reducing the firm’s survival rate.

As the impact of innovativeness has been widely examined in the literature we take into consideration this aspect in our paper. Even if we don’t have a proxy for innovative input, we consider patent granting as a proxy for innovative output.

2.3.6. Geographical Clusters

One of the most discussed aspects of business activities is the importance of geographical location. The effect of local proximity to similar firms has been observed in many different contexts in order to understand the mechanism of knowledge spillovers. Incumbent firms and start-ups active in the same industries share the same technologies and skills. Being located in the same geographical area gives them the advantage of creating clusters that connect them through externalities. Of course, knowledge spillovers are not homogeneous across firms.

According to the literature, the effects of agglomeration could be divided in direct external effects and indirect external effects. The former refer to localised knowledge spillovers (LKS), that means the positive effect of technical discoveries on the productivity of firms which didn’t make the discoveries themselves (Breschi and
Lissoni, 2001). This effect is bounded in space for firms located near the source of knowledge, more than firms located elsewhere. The latter effects refer to economies of intra-industry specialization, increasing returns to scale in supply of the same inputs and labour market economies.

Recent academic literature has found that clustered firms show higher innovative capacity than isolated firms (Porter, 1990; Baptista, 2000). In particular, in high-tech industries interaction and communication between companies are crucial to share new ideas, considering the tacit dimension of this type of knowledge. This is the reason why better innovations are more likely to be developed within the same geographical location, usually close to universities, research laboratories and other R&D institutions.

In 2007 Klepper, in contrast with the conventional theories of agglomeration economies benefiting co-located firms, explained the geographic concentration of the U.S. automobile industry with the disagreements within employees of the incumbent firms. He studied the agglomeration of the automobile companies around the area of Detroit and attributed it to four early entrants that spawned many successful spin-offs in the same area over the period 1895-1966.

As a result, in this thesis we decided to include a number of individual, organizational, and environmental factors measured at the beginning of the study to count for these additional determinants of survival.
3. The ICT Industry

Our analysis considers new firms in the Information and Communication Technologies industry. This section will first give the basic notions of ICT, that means understanding what generally is considered part of this industry and which kind of expressions we refer to. Then, we will introduce the context of our sample, the Swiss economy, with particular focus on the country ICT market.

3.1. Industry Definition

If on one hand it is possible to identify some of the principal elements of ICT, on the other hand, it is not simple to give a unique definition of the industry, because we are talking about sectors where a general and shared definition still doesn't exist. The existence of a widely accepted definition of the ICT industry is the first step in order to make comparisons across time and countries possible.

The Information and Communication Technologies industry could be considered a combination of several different sub-sectors that comprises not only telecommunications and hardware sector, but also the software industry, the internet and networking industry (Figure 1). ICT is a comprehensive framework for organizing all these related fields that share common knowledge and technologies but lead to different outputs.

Few years ago these industries could have been considered separate sectors, but as technologies relationships have changed, the boundaries have started to become less clearly defined.
The ICT producing sector is defined by Organisation for Economic Co-operation and Development as “all economic activities that produce goods and services facilitating the digitalization of the economy, which means converting information that is used or provided in electronic form that is easier to handle, communicate, store, recover, etc.” (OECD, 2002a).

For its nature, ICT sector is an extreme dynamic field that is going to face numerous evolution steps in a very short period, and the previous definition could be difficult to understand as technologies evolve. The best way to define ICT is taking into consideration the industries where it operates. The National Statistical Institute of Netherlands (CBS) gives a distinction between the two main operative fields of ICT: manufacturing and services. This definition is linked with the general one of the OECD, first released in 1998 and then revised slightly in 2002, and again in 2007 (ISIC Rev. 4).

Today we can distinguish between two main areas where ICT sector operates (European Commission, 2013): ICT Manufacturing industries (electronic components and boards, computer and peripheral equipment, communication equipment,
consumer electronics, magnetic and optical media), and ICT Service industries (wholesale of electronic and telecommunications equipment and parts, software publishing, wholesale of computers and software, telecommunications, computer programming and consultancy activities, data processing and related activities, web portals, repair of computers and communication equipment).

Thus, we can say that ICT ends with merging more and more the component of Information Technology (IT) with the one related to Communication Technology (CT). Even if this definitions could appear limited for the complexity and undefined boundaries of ICT sector, we chose this approach in order to give a clear idea of which companies are included in our sample.

The sector is highly innovative and subject to constant technological development. Following the discussion above, we can say that within ICT the type of innovators may vary considerably across different sectors. They can come from large multinational companies, from very small enterprises, or from universities and research institutions.

For this reasons, many authors have considered ICT as a General Purpose Technology (Bresnahan and Trajtenberg, 1995; Helpman, 1998) because they are used in many sectors of the economy. GPTs are radical innovations that have the potential to impact on many industries. Their key characteristics are: pervasiveness (used as inputs by many downstream industries), technological dynamism (potential for improvements), and innovation complementarities (the productivity of R&D in downstream markets increases as the GPT improves) (Vuijlsteke, Guerrieri and Padoan, 2007).

In this respect, ICT has allowed the emergence of many technologies and applications, across a huge range of sectors (Koumpis and Pavitt, 1999; Mahdi and Pavitt, 1997). One further characteristic of innovation in ICT is that it comes from long-term R&D collaborations between firms, across many different industries (Corrocher, Malerba and Montobbio, 2003).
3.1.1. Innovation in ICT

In general, R&D expenditures in the field of ICT are concentrated in the manufacturing sector, while IT services have gained ground during last years (OECD, 2013).

Patents play an increasingly fundamental role in innovation and economic performance of ICT. The growing importance of the sector as crucial source of technical change is reflected in the increasing number of patent applications. Most patent offices have experienced an increase in patent applications in the past two decades, with the largest contribution made by high technology industries (e.g. ICT and biotechnology). During the period 1991-2001 the share of ICT in EPO applications rose from 28% to 35% (OECD, 2003c). A similar increase was registered for patent applications at the USPTO during the same period.

The growing R&D expenditures have made a significant contribution to the innovation and thus to the rise of patent granting, but cannot fully explain it. In fact, universities and public research centres are sources of knowledge and technological domains for emerging technologies in ICT. In addition, the changes in competition have played a key role in the patenting trend in the ICT industry. For example, many authors have stressed the relevance of patent portfolios and strategic patenting for firms in the US semiconductor industry and EU mobile phone industry (Hall and Ziedonis, 2001). Moreover, changes in patent regimes made patents easier to obtain and more valuable. Again, the extension of the subject matter resulted in increasing patent applications for software and generic invention.

As a result, the change in patenting trend in ICT during last years could be explained both by the growth of inventions in new fields and the changes of the economic environment (Kortum, Eaton and Lerner, 2003; Kortum and Lerner, 1999).

3.1.2. ICT Trends

According to Gartner’s forecast several trends will be observed during next years in the ICT industry.
The key trend is the development of cloud computing services, that are now providing a central role for ICT convergence and a revolution in the way businesses operate in their fields (20% of business already own no IT assets). Telecommunications companies are now moving their IT systems and data centers into the cloud, lowering costs of buying and maintaining servers. Cloud computing also allows workforce located in different places to efficiently collaborate and exchange information easily.

Moreover, mobile phones will overtake PCs as the most common web access device and more than three billion of people will be able to transact electronically via mobile and internet technologies.

Finally, the topic of green IT is going to be central for the market and most IT business cases will include carbon remediation costs.

3.2. Context: The Swiss Economy

Switzerland is a federal parliamentary republic with a population of approximately 8 million people. It is located in the heart of Europe, however, it is a non-EU country. Research, education, and technological innovation are the main areas of excellence in the country. More than 50% of Switzerland’s GDP comes from foreign trade and more than a third of domestic demand for products and services comes from imports (Quayle, 2001). Considering business evolution, Switzerland consists of more than 300,000 small and medium size enterprises (SMEs) which counts for 95% of active firms (Quayle, 2001).

The excellent institutions, dynamic markets, and strong innovation potential led the country to perform first in economic competitiveness among 139 countries (World Economic Forum, 2013). The country, moreover, has implemented a long-term agenda in order to create the right economic environment for business activity, stimulated by the stable economic situation and the transparency of public institutions.
3.2.1. Innovation performance

In relation to innovation, Switzerland is in the first place in the ranking of both the European Innovation Scoreboard 2013 and the Global Innovation Index 2013, continuously outperforming all EU countries. Switzerland’s strong performance is linked to being among the top 3 performers for 15 indicators, in particular regarding the research system, firm investments, intellectual assets, and innovators. Relative weaknesses consist in having below average share of SMEs innovating in-house, financing support, and collaboration between entrepreneurs (OECD, 2013).

In the Global Entrepreneurship Monitor (GEM, 2009), the world’s leading research consortium dedicated to the understanding of the relationship between entrepreneurship and national economic development, Switzerland is included among the 20 innovation-driven economies. This classification in phases of economic development is based on level of GDP per capita. As innovation-driven economy, Switzerland is characterized by the introduction of new products and services using pioneering and sophisticated methods.

The relative strength of Switzerland in innovation performance is primarily due to the research system and the innovative output. It is the most active country in the OECD in terms of innovation, surpassing Japan and Sweden (GEM, 2009). However, the entrepreneurial propensity of its population and the cooperation between firms is below the international average, considering small-medium size enterprises (European Commission, 2013).

Switzerland performs better in R&D expenditures than the U.S. and the EU average, and research policy is characterized by continuity and stability. During the last decade, R&D investments increased with an annual average rate of 1.9% (EU average was 0.8%) (European Commission, 2013).

Today investment in research and development accounts for almost 3% of Swiss GDP, one third coming from the public sector and academic institutions, the other two thirds are spent by private companies. This is due to the structure of the Swiss economy, which is dominated by very large multinational companies with
global investment strategies. An important trend in public R&D expenditures, moreover, is the increasing investments for universities, with a percentage of 24.2% over the total expenditure and an average annual increase of 5%. This means that almost all public sector research is carried out in higher education institutions and public research policy is focused basically on applied-research universities.

ICT, pharmaceutical, and chemical industries account for the most part of the investments. Even if the majority of it is coming from large companies, small and medium enterprises have started increasing a lot their R&D expenditures during last years, thanks to the contribution of high technology products based on knowledge-intensive industries. SMEs with less than 250 employees (90% of the total) are very important for innovation activity, which is fundamental for the economy of a country (FSO, 2009).

For what concerns other innovation outputs, the number of doctoral graduates has increased from 2.7% in 2002 to 3.6% in 2009 (European Commission, 2013). As a result, in 2011 scientific publications were within the 10% most cited worldwide and there were 2,505 publications per million inhabitants. Best results in scientific production were achieved in the field of energy, environment, information and communication technology, and nanotechnologies.

3.2.2. Workforce and Entrepreneurship

Switzerland has one of the highest employment rates in the world (81.8% in 2011), compared to the EU average of 68.6% (OECD, 2011). This trend is associated with a high share of population with tertiary education (44% in 2011). The country occupation is divided into three main sectors: agriculture (less than 10% of population), industry (40% of population), and services (more than 50% of population). The high percentage of educated population (near 100% literacy) results in a very competent and qualified workforce.

During last decades Switzerland has been considered an employment paradise for the high performance of its job market, meanwhile most of the industrialized
countries have experienced serious financial and social crisis, linked to increasing rate of unemployment and decreasing real salaries.

In general, support for entrepreneurial activity is structured in several actions. The tax system is designed to attract investments and there is no capital gains tax (Tajeddini and Mueller, 2008). In addition, there are a lot of entrepreneurship awards for SMEs (e.g. Innovation Award, Entrepreneurship Award) rewarding economic efficiency, success, and degree of innovation. The result of making it relatively easy to start a new business, is that much Swiss entrepreneurship and innovation comes from outside (Kurzman, 2004; OECD, 2006; Shannon, 2000; Eckert, 2005), and the majority of business creators are coming from foreign countries (Krasna, 2003).

Considering the stimulating environment described above why is Switzerland still lacking entrepreneurs? OECD (2006) outlines that there are mainly four obstacles to the entrepreneurship in Switzerland.

First, the larger size of the domestic market after the elimination of local barriers, could stimulate firms to grow in some sectors. Second, the administrative burdens among cantons, end up limiting the cooperation among them. Third, the bankruptcy law, which extends indefinitely creditors’ claims against a bankrupt entrepreneur, results in higher risk aversion and less use of bank credits. Lastly, equity financing and venture capital still play a minor role in financing of innovation projects.

3.3. ICT Industry Profile in Switzerland

The Swiss ICT industry counted more than 16,000 companies in 2008, which represented 5% of all Swiss companies and is divided in five sectors: production, wholesale, retail, telecommunication and services (Sieber&partners, 2010).

However, the industry is essentially based on service activities (telecommunications and computer-based activities), which account for almost 75% of the sector (FSO, 2008). In particular telecommunications services have a strong influence on the whole economy of the country.
In relation to the structure of the market, 87% of the companies are very small (less than 10 employees), even if among the top 100 European ICT companies published by Red Herring (2009), there are 14 Swiss companies. Therefore, the industry is characterized by a fragmented structure, a dynamic market with fast product innovations, and a system of complementary parts (Sieber&partners 2010). The value chain in the ICT sector is divided up into production, trading of mass products, and services for the implementation of system.

This fragmentation has grown during recent years, increasing the replacing of individual solutions to customizable standard solutions. Successful ICT companies focus on two main business strategies: customer relations and product innovation (Sieber&partners, 2010).

Numerous studies have been done to better understand and measure the impact of the information and technology on the national economy. The most used information is the impact of the sector on gross domestic product (GDP). In general, all studies agree that the ICT sector has become a key factor in economic growth (FSO, 2008).

The gross added value of the ICT industry in 2006 accounted for 26.7 Billion CHF, which equals 5.5% of the Swiss GDP, and was forecasted to grow to 29.3 Billion by 2013, according to data released by industry group Swico and the EITO.

In 2005, more than 155,000 workers were employed in the ICT industry (4% of the Swiss workforce), most of them working in the IT services sector. The rapid expansion of ICT enterprises had a clear impact on the labour market, which experienced an average annual job growth rate of +6.6% over the period 1998-2006 (FSO, 2008). This phenomenon was particularly pronounced in the computer-related activities which showed a job growth rate of +15.9% between 1998 and 2001.

Switzerland has made a substantial effort to support the growth of a productive ICT industry. In order to indentify the characteristics of Swiss ICT environment we have to consider first the strengths of the country in relation to this sector.

First of all, the high skilled workforce represent one of the greatest advantage of the Swiss landscape. This workforce is focused on quality, as a result of experience in precision operations. The consequence of this fact is that Switzerland became one
of the most productive country in Europe. Second, the stable Swiss government and the growing economy is another strength that calls for huge investments coming from larger countries.

In February 1998, the Swiss government signed the beginning of a national ICT policy with the introduction of four guiding principles (The Strategy for an Information Society in Switzerland), that promoted technology access in school and businesses. During the same year, the Federal Assembly of the Swiss Confederation approved the Telecommunications Law that liberalized the Swiss telecommunications market (OFCOM, 1998).

After the liberalization of the telecommunications market, which contributed to the rise of new companies, was created the base for a strong market competition. From 2000, new operators engaged a price war in order to win the greatest market share. As a result, prices in the telecom sector dropped by 20.6% during the same years. This prices fall had the effect of rising the gross value added (GVA) of 27.2% in telecom sector in Switzerland. Of course, the fast growth was linked also to the birth of new fields and opportunities such as mobile phones and internet services.

All in all, these evolutions turned to a significant expansion of the ICT sector after 2000. To understand how strong is the effect of ICT sector to the economic growth in Switzerland we need to examine the contribution to GDP growth and the relative share of GDP (Table 1).

Table 1. ICT sector contributions to GDP growth, GDP trend and relative share in Switzerland (1998-2006)

<table>
<thead>
<tr>
<th>Year</th>
<th>ICT contribution</th>
<th>GDP trend</th>
<th>Relative share</th>
</tr>
</thead>
<tbody>
<tr>
<td>1998</td>
<td>0.5 %</td>
<td>2.6 %</td>
<td>19.2 %</td>
</tr>
<tr>
<td>1999</td>
<td>0.5 %</td>
<td>1.3 %</td>
<td>38.5 %</td>
</tr>
<tr>
<td>2000</td>
<td>0.8 %</td>
<td>3.6 %</td>
<td>22.2 %</td>
</tr>
<tr>
<td>2001</td>
<td>0.3 %</td>
<td>1.2 %</td>
<td>25.0 %</td>
</tr>
<tr>
<td>2002</td>
<td>0.2 %</td>
<td>0.4 %</td>
<td>50.0 %</td>
</tr>
<tr>
<td>2003</td>
<td>0.0 %</td>
<td>-0.2 %</td>
<td>-</td>
</tr>
<tr>
<td>2004</td>
<td>0.2 %</td>
<td>2.5 %</td>
<td>8.0 %</td>
</tr>
<tr>
<td>2005</td>
<td>0.3 %</td>
<td>2.5 %</td>
<td>12.0 %</td>
</tr>
<tr>
<td>2006</td>
<td>0.2 %</td>
<td>3.4 %</td>
<td>5.9 %</td>
</tr>
</tbody>
</table>

Source: FSO 2008
The table above shows the relation between GVA of ICT sector and the general GDP trend for Swiss economy on yearly base. For example, if we consider 2001 the ICT sector’s GVA growth represented +0.3% of the growth of GDP (+1.2%) of the same year. This means that the relative share of ICT sector growth over the GDP growth accounted for 25% in 2001. This is an enormous contribution considering the size of the industry. However we should consider that some other relevant sectors may have registered a negative contribution in the same years, reinforcing the relative effect of ICT sector to the growth of the economy.

In general, between 1998 and 2006, the ICT sector’s contributions to GDP were positive through the years (FSO, 2008). Despite its relatively small size, this sector made a significant contribution to the growth of the Swiss economy. Nonetheless, from 2003 there was a considerable decline of the ICT contributions to GDP growth. After the fast growth of the beginning of last decade, it experienced a more stable path. This is linked also to the end of restructuring waves which the Swiss economy faced. Today, the ICT is the fifth most important industry of the country, with increasing number of companies becoming international offering innovative solutions (FSO, 2009).

3.3.1. ICT Geographic Clusters

In Switzerland clusters have occurred naturally, as the result of partnerships between the higher education institutions and companies. Of course, ICT is not the only sector characterized by the creation of clusters. Biotechnology, pharmaceuticals and medical technology are only three examples of industries that promoted their research and development activities in collaboration with universities. The government’s role is focused on facilitating the creation of the best possible conditions for businesses to operate. The excellent work done by leading research centres (e.g. EPFL in Lausanne and ETH in Zurich), and the supporting work of administrative organizations during the last decade, has created regions that served as nursery for ICT actors. This was possible thanks to political and educational programmes and incentives to encourage the development of competences.
3.3.2. ICT Financing

Since 1986, the Swiss ICT sector has benefited from the incentive programs promoted by the government. One of the major benefit was a 10 years of no-tax program for less developed areas, and investments in private-public partnerships.

As discussed above, during the first part of last decade, the business sector provided more than 60% of the funding for domestic R&D, while universities and other research institutions were responsible for one third of founding during the same time period, confirming the central role of higher education institutions to increase the knowledge base and find commercial applications for their research (OECD, 2001).

The STI Scoreboard found that venture capital market in Switzerland is a small percentage of national GDP (less than 2%), even if VCs are responsible for the majority of investments in high technology firms. The report underlines also that venture capital focus their financing in biotechnology firms, whether ICT represents around 20% of their investment. According to the Global Entrepreneurship Monitor, Venture Capital investments in Switzerland were less than 0.05% of GDP during 2009, considering all stages of Venture Capital. The percentage falls to 0.03% if we consider only investments in seed, start-up, and early-stages ventures (GEM, 2009).

In general, more than 20 Billions CHF are invested in ICT yearly (FSO, 2009). Looking at the different area of investment, the greatest amount went to data storage and processing services (43%), followed by measuring, control and regulation technologies (24%). Communication technologies accounted for 22%, and information technologies only obtained only 11% of the total investments.

Large investments in the ICT industry are a competitive advantage for the country, as the modernization of the existing infrastructures, the integration of new technologies, and the convergence of ICTs will contribute to increase the economic productivity (Bertschinger and Haisch, 2010).

In the next chapter we will present the dataset and the methodology.
4. Data and Method

In this section we describe the dataset and the method followed to build it. The main variables are explained and preliminary statistics analysis are included. In the end, some Kaplan-Meier estimates are reported and the econometric models used in the analysis are described.

4.1. Data Sources and Variables Definition

In this paper we rely upon an original dataset of 353 Swiss start-ups, founded between 2000 and 2013. The new firms were all active in the ICT industry and based on the list provided by Startupmonitor.ch, a single, independent, and trusted database for secure capturing and sharing of start-up performance data.

For these firms, we collected information on: company name, entry year, eventually exit year (either by liquidation or by acquisition), geographical location, university affiliation, venture capital support, patents granted, name, education and background of the founders.

Due to the lack of information, a limited number of firms were excluded from the initial dataset, in order to avoid incomplete analysis. The final dataset is composed of 259 firms.

The main sources of information were the Swiss Commercial Registry and Moneyhouse, which is the most used web portal for updated data on firms. From these sources we collected information on entry and exit date, addresses, financials and name of the founders.

Information concerning main sectors of activity were collected from Monetas.ch, a certificated database of Swiss companies that gives updated business register information. In particular NOGA codes, for all founded firms and companies where the founders were working before, are collected from this source. The NOGA 2008 code (Nomenclature Gènèrale des Activitès économiques) is an essential tool for structuring, analyzing and presenting statistical data. It is a classification system which divides firms according to their economic activity and arranges it in coherent groups. Once a new firm is registered in the Commercial Register, a NOGA code is
assigned by the Swiss Federal Statistical Office according to the purpose of the business.

Other information related to university affiliation and venture capital support were collected from StartUp.ch, a platform for Swiss start-ups that gives the opportunity to present themselves and get in contact with investors and experts. The website is provided by the IFJ (Institut Für Jungunternehmen), an organization that supports and promotes young entrepreneurs since 1989.

Thanks to the PATSTAT-KITES database of Bocconi University, we were able to collect information about patents granted to these firms by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO), with the relative number of forward citations. For USPTO patents a data cleaning procedure was followed in order to eliminate matching errors.

Finally, additional information on founders’ education and background were collected from other online sources such as LinkedIn, Zoom Info, Bloomberg BusinessWeek and, whenever was possible, further information were extracted from companies’ websites.

Firms in the sample were first classified based on their founders’ background. This process was carried out considering the pre-entry experience of each founder (the main sector of the firm where they were working before establishing the new venture was taken into account). We focused on the background of the founders and not on other employees, for which data were not available. The implicit assumption is that founders affect profoundly the orientation of their start-ups and determine their know-how. For the purpose of this classification, we first used NOGA codes, in order to identify with a certain accuracy the business activity. Considering that NOGA codes were not sufficient to understand the relation between previous companies where founders worked and the new ventures, we had to analyze individually each company website. That means, we collected information on the business activity of the firms and, based on that, we understood which kind of relationship there was with the previous working experience of each founder. Based on these assumptions, 5 categories were identified.
A number of firms were founded by entrepreneurs who were all previously working as professors, researchers or Ph.D. students in a higher education institution, such as the Swiss Federal Institute of Technology of Zurich (ETH) or the Ecole Polytechnique Fédérale de Lausanne (EPFL). We called these firms University Start-ups. In total 45 University Start-ups were identified.

Other firms were founded by entrepreneurs who were all previously working in a ICT company. We considered in this category mostly companies with activities related to computer consulting, computer programming, web portals, and other information technology and computer service activities. We called these firms Spin-Offs. In total 84 Spin-Offs were identified.

One further category of firms were founded by entrepreneurs who were all previously working in companies that rely heavily on the products or knowledge produced in the ICT sector (e.g. Bridge Solutions AG is a company that develops logistic software and the founders were all working for delivery and transport companies). Of course, these founders had some industry related knowledge but they should be distinguished from classic spin-offs because they worked for a potential user or customer of the new business. We defined firms in this category as Demand Spin-Offs. In total 29 Demand Spin-Offs were identified.

Another group of start-ups was founded by individuals with less related experiences. In this category we included both firms founded by all completely inexperienced people or all previously active in unrelated fields such as banking, law, consultancy, and finance. We called these firms Inexperienced Start-Ups. A total of 58 Inexperienced Start-Ups were identified.

Lastly, other firms were founded by a mixed background team (e.g. one founder coming from the ICT industry, another from University, and a third one with no previous experience). We called these firms Mixed Start-Ups. A total of 43 Mixed Start-Ups were identified.
Firms with just one founder were easy to classify. Firms founded by a team were classified in one of the first four categories if the majority of the founders had been working in a University Start-up, in a Spin-Off, in a Demand Spin-off, or Inexperienced Start-up. When there was a firm with founders having different professional backgrounds, the firm was classified as Mixed Start-Up.

4.2. Descriptive Analysis

Between 2000 and 2013, on average around 19 firms entered the industry each year, with a concentration during the period 2008-2011 (Table 2). In particular, 148 new start-ups were founded during these 4 years (57%). Entry of new firms started slowly between 2000 and 2005 (53 firms in total), accelerated from 2006, reaching the highest value of 42 new entrants in 2011, and then started decreasing. This result shows that, even if the economic crisis was quite tough in that period, the Swiss ICT industry has not been affected. During recessions some people may see new opportunities to start businesses given the change in their circumstances. Several theories found that the best innovations have been initiated in times of recession, when societies were more willing to change.

In our sample, only 30 firms out of 259 exited the industry (11.6%), with the bulk of exits concentrated in the last 3 years considered. Among the exited firms, 15 failed and 15 were acquired during the entire period. Considering the survival period of the ventures in the dataset (that is right censored on November 2013), we have an average duration of 5.19 years, with a minimum value of 0.45 years and a maximum of 13.84 years. The big difference between the extremes values in a sample of start-ups from the same industry and the same country reinforces the importance to find the right determinants for the success of someone and the failure of others.

Detailed information regarding entry and exit time distribution are reported in the Appendix (Figure 2).
### Table 2 – Entry, exit and firm background

<table>
<thead>
<tr>
<th>Year</th>
<th>N. of Entry</th>
<th>N. of Exit</th>
<th>% of Entry</th>
<th>% of Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>9</td>
<td>3</td>
<td>3%</td>
<td>0%</td>
</tr>
<tr>
<td>2001</td>
<td>10</td>
<td>3</td>
<td>4%</td>
<td>0%</td>
</tr>
<tr>
<td>2002</td>
<td>6</td>
<td>1</td>
<td>2%</td>
<td>0%</td>
</tr>
<tr>
<td>2003</td>
<td>12</td>
<td>5</td>
<td>5%</td>
<td>0%</td>
</tr>
<tr>
<td>2004</td>
<td>8</td>
<td>3</td>
<td>3%</td>
<td>0%</td>
</tr>
<tr>
<td>2005</td>
<td>8</td>
<td>3</td>
<td>3%</td>
<td>0%</td>
</tr>
<tr>
<td>2006</td>
<td>11</td>
<td>4</td>
<td>4%</td>
<td>0%</td>
</tr>
<tr>
<td>2007</td>
<td>22</td>
<td>1</td>
<td>8%</td>
<td>3%</td>
</tr>
<tr>
<td>2008</td>
<td>32</td>
<td>12</td>
<td>12%</td>
<td>0%</td>
</tr>
<tr>
<td>2009</td>
<td>37</td>
<td></td>
<td>14%</td>
<td>0%</td>
</tr>
<tr>
<td>2010</td>
<td>37</td>
<td>1</td>
<td>14%</td>
<td>3%</td>
</tr>
<tr>
<td>2011</td>
<td>42</td>
<td>7</td>
<td>16%</td>
<td>23%</td>
</tr>
<tr>
<td>2012</td>
<td>24</td>
<td>9</td>
<td>9%</td>
<td>30%</td>
</tr>
<tr>
<td>2013</td>
<td>1</td>
<td>12</td>
<td>0%</td>
<td>40%</td>
</tr>
<tr>
<td>Total</td>
<td>259</td>
<td>30</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Looking at the different types of new entrants (Table 3), University Start-ups and Inexperienced Start-ups showed the highest exit rate (17.8% and 13.8% respectively). Spin-offs and Demand Spin-offs, on the other hand, were the more likely to survive with only 9.5% and 6.9% of exits. Finally, Mixed Start-ups were in line with the Spin-offs (9.3%). All in all, approximately 32% of the firms belongs to the Spin-offs category, followed by Inexperienced Start-ups (22%). University Start-ups account for 17% of the total, Mixed Start-ups for 16%, and Demand Spin-offs are only 11% of the sample.

### Table 3 – Exit by Types of Start-ups

<table>
<thead>
<tr>
<th>Type</th>
<th>Liquidation</th>
<th>Acquisition</th>
<th>Exit</th>
<th>Total</th>
<th>% of Exit</th>
</tr>
</thead>
<tbody>
<tr>
<td>University Start-ups</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>45</td>
<td>17,8%</td>
</tr>
<tr>
<td>Inexperienced Start-ups</td>
<td>4</td>
<td>4</td>
<td>8</td>
<td>58</td>
<td>13,8%</td>
</tr>
<tr>
<td>Spin-offs</td>
<td>5</td>
<td>3</td>
<td>8</td>
<td>84</td>
<td>9,5%</td>
</tr>
<tr>
<td>Mixed Start-ups</td>
<td>2</td>
<td>2</td>
<td>4</td>
<td>43</td>
<td>9,3%</td>
</tr>
<tr>
<td>Demand Spin-offs</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>29</td>
<td>6,9%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>15</strong></td>
<td><strong>15</strong></td>
<td><strong>30</strong></td>
<td><strong>259</strong></td>
<td><strong>11,6%</strong></td>
</tr>
</tbody>
</table>
In addition to the former variables capturing the background of the start-ups, we decided to include in the analysis a list of control variables concerning the founding team characteristics, the universities affiliation and venture capital support, the innovativeness, and the geographical location of the companies.

4.2.1. Founding Team

According to the existing literature, the team of founders is a determinant of new firms’ performance and survival. As discussed by Cooper and Bruno (1977), multiple founders team have higher probability of survival than single founders.

In particular, in our sample, 72 firms have been founded by a single founder (28%), 98 firms by two founders (38%), 65 firms by three founders (25%), 17 firms by four founders (7%), and only 7 by five founders (3%). Additionally, we included a dummy variable (Founded by team) that is equal to one if the firm was established by more than one founder. As we can easily understand the majority of the new firms were founded by a multiple founders team (72%).

Moreover, previous studies have pointed out that teams with a mixed educational background are more likely to survive longer because they can combine knowledge coming from different field of studies and have different perspectives. For this reason, we included a dummy variable (Mixed edu background) that is equal to one if the firm has founders with different educational background (e.g. Engineering and Business studies). Due to the lack of information regarding the educational background of some founders, we reduced the sample at 238 observations, finding that 78 firms are identified among those whose founders have a mixed background (33%).

An additional factor stressed by many authors, is the role of the educational level of the founders as determinant of survival of new firms. Empirical evidences, in particular in the high technology industries, showed that the majority of the entrepreneurs have at least a Bachelor or a Master degree (Robert, 1991). Moreover, holding a Ph.D. positively affects the probability of survival for new firms because doctoral studies provide a competitive advantage over the other firms. As a
result, we included an additional dummy variable \((Ph.D.)\) that is equal to one if at least one of the founders holds a doctorate degree. Over the restricted sample of 238 observations, we found that 96 firms have at least one founder with a Ph.D. (40%).

Since the field of studies is as important as the level, we included also a dummy variable \((Edu\text{ field related})\) that is equal to one if the educational field of at least one of the founders is related to the ICT industry (e.g. Computer Science, Engineering, Information Technology). 171 firms out of 223 were found to have at least one founder with an educational background related to the ICT (77%). This is consistent with the standard viewpoint that technical knowledge is important for the success of a high technology business.

As discussed in the chapter of literature review, serial entrepreneurship is another important determinant of firm survival rate. In fact, having prior business experience that characterizes a founder as serial entrepreneur, in general is associated with relatively lower hazard rates compared with firms founded by people with no previous business experience. The reason is that they are more capable of identifying new valuable opportunities and have better responses to problematic situations, because they have already experienced it before. Some other authors, however, showed that serial entrepreneurship could be associated with less motivation and underestimation of problems, which leads to higher risk of failure (Ucbasaran et al. 2003; Simon et al. 2000).

A dummy variable named \((Serial\text{ Entrepreneur})\) was included in order to understand better the direction of the relationship with survival period. The variable assumes the value one if at least one of the founders has previously founded a firm. We found 106 firms characterized by the presence of a serial entrepreneur (41% of the sample).

In addition, the age of the founders is another important variable that should be taken into consideration. The common view is that older individuals are more experienced than younger one, and as a consequence have more chances to survive. This is clear in almost all industries, because there are many capabilities and
know-how that need years of experience to make a difference in terms of performance. Nonetheless some authors, Cooper (1986) and Roberts (1991) among others, have stressed the successful role of young entrepreneurs in fast moving industries such as high technologies. In fact, very young individuals have a number of advantages that clearly constitute a competitive advantage: they are more creative, more likely to see new applications for existing technologies, faster in learning how to develop new products, less adverse to risk, and more flexible than older entrepreneurs. This is consistent with the previous literature that found a median age for entrepreneurs ranging from 28 to 39 years old (Roberts, 1991).

In an attempt to address to this topic we created a dummy variable ($\text{Age}>40$), that is equal to one if at least one of the founders has more than 40 years old. The observations available were 240, and the number of firms with at least an entrepreneur over 40 are 141 (59%).

Recently, the role of entrepreneurial mobility has emerged. Empirical studies underlined that high-skilled scientists and engineers started to move outside their home country to establish business activities. This mobility is fundamental to facilitate knowledge transfer and exchange of technologies. On the other side, scientists that have accumulated years of experience abroad, might want to come back home, in order to spend the acquired know-how for their country of origin.

Results show that 173 firms out of 240 were established by teams that studied in Switzerland (72%), proving that in this industry the relationship between universities and entrepreneurs is very close. Switzerland is worldwide renowned for the quality of its higher education, in particular engineering schools, such as ETH and EPFL, where most of the founders of our dataset come from.

A further topic of discussion among authors is the influence of team of founders coming from the same previous company on the performance of new ventures. Cooper and Gimeno-Gascon (1992) conjectured that a spin-off’s heritage will affect its performance. Spin-offs with more than one founder coming from the same parent organization are expected to have retained some sort of shared routines, eventually leading to better performance. Moreover, they might know each other and probably
chose to leave the parent company because already working on a new idea that they want to patent. Cooper (1985) found that multiple founders that worked together in the same organization are more likely to survive.

To control for this, a dummy variable (Team Spin-offs) has been included in the sample, that is equal to one if two or more founders came from the same company. Of course, only multiple founding teams are considered in the analysis, and university start-ups have been always considered team spin-offs, because coming from the same organization. A total of 98 team spin-offs were identified (38% of the sample).

In addition to the former variables capturing team characteristics, we included in the analysis a measure for firm size. As a result we chose the number of employees as a proxy for firm size and created a category variable.

Confirming the information reported on the Swiss ICT industry, we found that the majority of the start-ups (54%) in the sample are very small companies, with only 9% of the firms having more than 50 employees (Table 4).

Table 4 – Firm size distribution

<table>
<thead>
<tr>
<th>N. of Employees</th>
<th>N. of firms</th>
<th>% of firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-10</td>
<td>99</td>
<td>54%</td>
</tr>
<tr>
<td>11-50</td>
<td>69</td>
<td>38%</td>
</tr>
<tr>
<td>51-200</td>
<td>14</td>
<td>8%</td>
</tr>
<tr>
<td>&gt; 500</td>
<td>2</td>
<td>1%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>184</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

4.2.2. University Affiliation and Venture Capital Support

Support from private or public institutions constitutes an important determinant for start-ups success. European Union, National Government, Universities and Venture Capital firms are all potential sources of financial support and other form of support, such as training and mentoring.
Many Swiss start-ups receive different kind of support and services from local universities, in particular the category of university start-ups. In Switzerland there are three types of institutions of higher education: regional universities of applied sciences financed by the respective region and in part by the federal government, cantonal universities financed by the respective canton, and federal universities financed by the federal government (Arvanitis, Kubli, and Woerter, 2008). The two federal technical universities (ETH and EPFL) are the more research-oriented institutions for applied sciences and during the last decades they began to promote the formation of new science-based ventures (so called University Spin-offs).

However, typical university spin-offs are not the only possible result of support from research institutions. Based on data available from the web portal Startupmonitor we created a dummy variable (University Affiliation) that takes into consideration all other services offered by universities. To better understand the difference between university start-ups and university affiliation we have to clarify what are the possible interpretations of this category. Where in the first case the founders are all coming from the university as professors, doctoral students, or researchers (typical definition of University Spin-off), in the second case there are two possible links between the company and the university:

1. the start-up gets monetary support from the university in terms of sponsorship or awards for a competition;
2. the start-up gets ideational support or mentorship from the university.

Surprisingly, we found that 124 of the firms in the sample (50%) are somehow linked to a university, confirming their role of promoter for local entrepreneurship. In particular, the two Federal Institutes of Technology (ETH and EPFL) together represent 63% of the affiliations (38% and 25% respectively).

As explained above, another important source of support for new ventures are VC firms. The last published report of Verve Capital Partners (investiere.ch) showed that Switzerland is the first European country for VC funding per capita (69$). A figure which is even higher than U.S. (67$). However, we must remember that these
figures are averages and the strength of life sciences industry affects it. In the ICT industry is still difficult for companies to find financial capital, as the failure of promising companies such as AXSionics AG showed (Wagner and Laib, 2011).

Among others agents, the Commission for Technology and Innovation (CTI) has always encouraged and subsidized the transition of science to market. The CTI is the innovation promotion agency of the Swiss Federal Government and has the role of supporting R&D projects, entrepreneurship, and development of start-ups (Commission for Technology and Innovation CTI.ch). In particular, CTI promotes market-oriented R&D projects, promotion of start-up companies, and technology transfer. VentureLab, VentureLeaders, and VentureKick are the three major programs developed or supported by the CTI during last years.

VentureLab was launched in 2004 as a national training program for innovative start-ups in the high-tech industry. Participants to the program are selected based on their personal profiles and the quality of their business idea. Seventy-two of the top 100 start-ups in Switzerland are included in the VenturLab program, many of them raising capital from external investors and expanding internationally (Venturelab.ch).

The VentureLeaders program, on the other hand, is an additional opportunity for a few Swiss entrepreneurs to see the U.S. market, as the first step to their global expansion. Each year over 100 start-ups apply to participate to the program and only the top 20 are selected to benefit from this training that is part of VentureLab experience. Start-ups that take part of this project have the opportunity to sign major contracts with strategic partners and investors as well as expand their customers’ base. During ten days of business trip, members of the team present their project in front of investors and industry experts (Venturelab.ch).

Lastly, VentureKick is a private initiative launched in the fall of 2007 by private foundations. The program consists of a three stage funding model in order to support Swiss start-ups with 130,000 CHF per project. After each stage, entrepreneurs are also offered professional guidance in developing their business thanks to a pool of over 100 leading start-up experts across Switzerland. Since the launch of the program, more than 10 Million CHF have been invested, and over 250 start-ups projects have been financed, generating a volume of 365 Million CHF and 2,000 new jobs created (Venturekick.ch).
In order to understand the effect of venture capital support to firms’ performance we created three dummy variables equal to one if the firm participated to one of the programs presented above. In total, 63% of the firms in our sample took part in one of the three federal programs, 51% of the firms participated in VentureLab, 19% participated in VentureLeaders, and 26% in VentureKick program.

4.2.3. Innovativeness

Very interesting is the analysis of the relationship between innovators and non-innovators among new entrants in the Information and Technology industry. As underlined in the literature review, innovation has a positive effect on the performance of new entrants in different industries. Through innovative activity (e.g. R&D, new products announcements, and patent granting), firms improve their productivity and their chances of success in the competitive environment. In highly innovative industries, such as ICT, the likelihood of survival over a decade is lower than other industries and depends mainly on the rate of innovation.

We decided to explore this possibility in the context of our sample. For the purpose of the study, data on innovative input were not readily available, but we used patent granting data as a proxy for innovativeness even if there are some limitations connected to the use of such instrument in the ICT industry.

In fact, patents play a key role in sectors as the pharmaceutical and chemical one, but have a very limited role in fast changing sectors such as ICT. Previous studies (Levin et al., 1987; Cohen et al., 2000; Bessen and Meurer, 2008) showed that some firms prefer to use other mechanism of strategic appropriation (e.g. lead time and secrecy). The nature of the innovation and the degree of competition among innovators shapes the propensity to use secrecy instead of patents (Hall et al., 2012). Moreover, the general purpose characteristic of ICT is responsible for the emergence of innovations in numerous technological domains, so that is difficult to assign a specific patent that refers to a given class (Corrocher, Malerba, and Montobbio, 2007). However, the growth in patent applications during last years is mostly explained by the increased patenting rate in the ICT industry (Hall, 2004). Large firms started to patent their innovation even if patents are deemed as not effective,
compared to other means (this is often referred to as the “patent paradox”). Cohen et al. (2000), in fact, found that firms use patents for strategic reasons (e.g. block competitors, increase reputation, improve bargaining power), rather than for protecting their intellectual property.

In general, patent granting and forward citations have been considered a good proxy for firms’ innovativeness in the past. Generally, patent counts has been accepted as an appropriate innovative indicator for firms, linked to new products and technologies. In the context of high technology industries, even authors that were critical on the use of patent as innovativeness indicator (Arundel and Kabla, 1998; Mansfield, 1986), admitted that patent could be appropriated as performance indicator. Additionally, patent citations is also increasingly used to measure inventive performance of firms. Compared to the simple patent counting, indeed, this indicator accounts also for a quality measure of patents. A lot of studies found evidence of the validity of patent citations as a good proxy for innovativeness, assuming that there is a positive relationship between the number of forward citations and the importance of a patent (Hagedoorn and Cloodt, 2003).

Cockburn and Wagner (2007) examined the effect of patenting on the survival in the internet industry, assuming that patents conferred competitive advantages to new ventures and are a signal for firm quality. Controlling for age, financial characteristics and VC backing, they found that patenting is positively associated with survival.

Moreover, Hagedoorn and Cloodt (2003) used a variety of indicators to measure the innovative performance of firms (R&D inputs, patent counts and patent citations). The strong overlap between these indicators shows that future research might also consider only one of these indicators.

As a result, we created a dummy variable for firms that have been granted patents by the EPO or by the USPTO, and for the number of forward citations.

Only 26 firms have been granted patents by the EPO or the USPTO (10% of the total sample). Among these firms only 11 hold a patent that has been cited forward (4%), confirming the hypothesis that patent granting is not a priority for start-ups in the ICT sector. Moreover, the majority of the firms that have been granted a patent hold only one or two patents (10 and 5 firms respectively).
4.2.4. Geographical Location

The importance of local proximity and the positive effect related to knowledge spillovers has been analyzed in the previous chapters. In our dataset we reported information regarding geographical location of every company and interesting results emerged.

Switzerland is composed by 26 cantons, with Zurich, Bern, Vaud, and Aargau accounting for the biggest one in terms of population. Our firms are located across 21 cantons but almost 64% of the total number of firms are concentrated in the canton of Zurich and Vaud.

As we can see from the Appendix (Table 5), 111 new entrants are located in the canton of Zurich (almost 43%), and 54 new entrants are located in the canton of Vaud (almost 21%). All the other firms (94) are spread across 19 different cantons. Our results are confirmed by the report of Startupmonitor.ch, that shows the geographical distribution for all the Swiss ICT companies, not only the 259 firms of our sample (Figure 3).

Figure 3- Geographical distribution: all Swiss ICT companies

Source: startupmonitor.ch
The presence of the ETH in the Zurich area and the EPFL in the canton of Vaud is clearly linked to this cluster formation, as the two main research institutions for applied sciences of the country have a pivotal role for entrepreneurs, scientists, and investors.

Summary descriptive statistics and correlations matrix for all the explanatory variables introduced are reported below (Table 6 and Table 7).

**Table 6 – Descriptive statistics summary**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>N. of firms</th>
<th>% of firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Founded by team</td>
<td>259</td>
<td>187</td>
<td>72%</td>
</tr>
<tr>
<td>Mixed edu background</td>
<td>238</td>
<td>78</td>
<td>33%</td>
</tr>
<tr>
<td>Ph.D.</td>
<td>238</td>
<td>96</td>
<td>40%</td>
</tr>
<tr>
<td>Edu field related</td>
<td>223</td>
<td>171</td>
<td>77%</td>
</tr>
<tr>
<td>Serial Entrepreneur</td>
<td>259</td>
<td>106</td>
<td>41%</td>
</tr>
<tr>
<td>Age &gt; 40</td>
<td>240</td>
<td>141</td>
<td>59%</td>
</tr>
<tr>
<td>Edu location=Startup location</td>
<td>240</td>
<td>173</td>
<td>72%</td>
</tr>
<tr>
<td>Team Spin-offs</td>
<td>259</td>
<td>98</td>
<td>38%</td>
</tr>
<tr>
<td>University Affiliation</td>
<td>250</td>
<td>124</td>
<td>50%</td>
</tr>
<tr>
<td>VC Support</td>
<td>170</td>
<td>107</td>
<td>63%</td>
</tr>
<tr>
<td>VentureLab Support</td>
<td>170</td>
<td>87</td>
<td>51%</td>
</tr>
<tr>
<td>VentureLeaders Support</td>
<td>170</td>
<td>33</td>
<td>19%</td>
</tr>
<tr>
<td>VentureKick Support</td>
<td>170</td>
<td>44</td>
<td>26%</td>
</tr>
<tr>
<td>EPO or USPTO Patent</td>
<td>259</td>
<td>26</td>
<td>10%</td>
</tr>
<tr>
<td>Patent Citations</td>
<td>259</td>
<td>11</td>
<td>4%</td>
</tr>
</tbody>
</table>
4.2.5. Kaplan-Meier estimates

In order to perform additional descriptive results we included some Kaplan-Meier estimates for specific parametric and categorical variables.

The estimator of Kaplan and Meier (1958) is a nonparametric estimate of the survival function $S(t)$, which is the probability of survival after time $t$ or, in another way, the probability of failing after $t$. For a dataset with observed failure times, the K-M estimate at any time $t$ is given by

$$\hat{S}(t) = \prod_{(j | \tau_j \leq t)} \left( \frac{n_j - d_j}{n_j} \right)$$ (1)

where $n_j$ is the number of firms at risk at time $t_j$ and $d_j$ is the number of failures at time $t_j$. The product is over all observed failure times less than or equal to $t$ (Cleve, Gould, Gutierrez, and Marcheko, 2002).
Figure 4 reports the Kaplan-Meier survival distribution for our sample. Firms that exited by being acquired are treated as censored exits, even if this assumes that acquisition and liquidation has the same negative meaning.

**Figure 4 – Kaplan-Meier survival estimate**

![Kaplan-Meier survival curve](image)

Considering the specific characteristics of the founders, we can see that multiple founder teams have a lower hazard of exit after the first 2.5 years, compared with teams of single founder (Figure 5).

**Figure 5 – Kaplan-Meier survival estimate (Founded by Team)**

![Kaplan-Meier survival curve](image)
Usually teams tend to include members with mixed educational background, including experts in scientific fields and experts in business, management or law.

Figure 6 shows that this is the right choice, as firms founded by mixed background teams survive longer than other firms founded by single or multiple founders.

**Figure 6 – Kaplan-Meier survival estimate (Mixed Edu Background)**

Additionally, having a doctoral degree seems to affect positively the survival rate of start-ups in our sample (Figure 7). The survival curves of teams with at least one member that owns a Ph.D. and teams without a Ph.D. overlap closely until about age 5 and then separate quite sharply.
Surprisingly, the inclusion of founders which had a previous business experience (Serial Entrepreneur), decrease the probability of survival of new entrants, at least after 2.5 years (Figure 8). However, there is no clear impact of this variable on survival. As discussed before, this result could be explained by the hypothesis that portfolio entrepreneurs may be over confident and less motivated than novice entrepreneurs. In addition, those who had already experienced failures in previous ventures may be more likely to fail again in the future.
For what concerns founders coming from the same previous company (Team Spin-offs), there are no clear difference in the survival until age 5. After this period team spin-offs have much higher survival rates than no team spin-offs (Figure 9). Last result confirms the conjecture that shared experiences and knowledge positively affect the performance of new ventures.

**Figure 9 – Kaplan-Meier survival estimate (Team Spin-offs)**

With regard to the support from Venture Capital firms, the Kaplan-Meier estimates suggest that both firms that received support from Venture Lab and Venture Leaders programs (Figure 10 and Figure 11) have a higher survival rate than those who do not have any support, from the first year considered.

On the other side, the result for the participation to Venture Kick program is not significant and thus is not reported.
Moreover, innovativeness seems to be another important determinant of survival in our sample. The survival curve of firms that neither hold an EPO patent nor an USPTO patent is much steeper at every age than the survival curve of firms that hold at least one patent, reflecting a lower hazard of exit at every age for innovative firms (Figure 12).
Finally, clusters of firms located in the same geographical area confirm that effects of aggregation and, among others, knowledge spillovers, affect the survival of new entrants. We divided our sample according to the location of the business between firms founded in the Zurich or Vaud canton and firms founded in other cantons. Results show that after the first 5 years, the probability of survival of firms located in the cluster of Zurich or Vaud is much higher than the other firms (Figure 13).

**Figure 12 – Kaplan-Meier survival estimate (Innovativeness)**

![Kaplan-Meier survival estimate (Innovativeness)](image)

**Figure 13 – Kaplan-Meier survival estimate (Geographical Location)**

![Kaplan-Meier survival estimate (Geographical Location)](image)
To further check our preliminary results, in the following part will be presented an econometric analysis to understand the implications of our findings and make some conclusions.

4.3. Methodology

To study the performance of the firms in our dataset we have carried out a survival analysis. Our econometric model consists in the estimation of a continuous time Cox regression model and a complementary log-logistic discrete time model.

4.3.1. The survivor and hazard functions

Let T be a non-negative random variable denoting the time to a failure event. The unconditional probability of failing at time $t$ is given by the following probability mass function

$$f(t) = \Pr(T = t_i)$$

(2)

The probability of surviving beyond time $t$ (survival function) is given by

$$S(t) = \Pr(T \geq t_i) = 1 - F(t)$$

(3)

The function is equal to one at $t=0$ and decreases toward zero as $t$ goes to infinity. The hazard rate, which represents the instantaneous rate of failure is

$$h(t) = \frac{f(t)}{S(t)}$$

(4)

It is the probability that the failure event occurs in a given interval, conditional upon the subject having survived to the beginning of that interval, divided by the width of the interval (Cleve, Gould, Gutierrez, Marcheko, 2002).
4.3.2. The Cox proportional hazards model

The Cox proportional hazards regression model (Cox, 1972) asserts that the hazard rate for the $j$th subject in the data is

\[ h(t|x_j) = h_0(t) \exp(x_j \beta_x) \]  

where the regression coefficients $\beta_x$ are to be estimated from the data. This model is semiparametric, in fact it makes no assumptions about the shape of the hazard over time. What is assumed is that, whatever the general shape, it is the same for everyone. The hazard of each subject is a multiplicative replica of another’s. Comparing subject $j$ to subject $m$, the model assumes that

\[ \frac{h(t|x_j)}{h(t|x_m)} = \frac{\exp(x_j \beta_x)}{\exp(x_m \beta_m)} \]  

which is constant, considering that the covariates $x_j$ and $x_m$ do not change over time.

The estimation is still possible even after leaving the baseline hazard function unspecified, and this offers a big advantage when we are not able to make assumptions about the shape of the hazard.

The Cox model has no intercept because it is subsumed into the baseline hazard $h_0(t)$. If we assume to add an intercept to the model,

\[ h(t|x_j) = h_0(t) \exp(\beta_0 + x_j \beta_x) \]  

thus

\[ h(t|x_j) = \{h_0(t) \exp(\beta_0)\} \exp(x_j \beta_x) \]  

where $\{h_0(t) \exp(\beta_0)\}$ is our new baseline hazard. The value of $\beta_0$ is undefined because any value works as well as any other; it would only change the definition of $h_0(t)$, which we do not define anyway.
For this model exponentiated individual coefficients have the meaning of the ratio of the hazards for a 1-unit change in the corresponding covariate (Cleves, Gould, Gutierrez, Marcheko, 2002).

4.3.3. Complementary Log-Logistic Model

Following Jenkins (2005), the complementary log-logistic model assumes that the survivor function at the end of the $t^{th}$ interval is

$$S(t, X) = \exp \left[ - \int_0^t \theta(u, X) du \right]$$

(9)

We also assume that the hazard function satisfies the proportional hazard specification

$$\theta(t, X) = \theta_0(t)e^{\beta X} = \theta_0(t)\lambda$$

(10)

where $\beta$ is a vector of coefficients to be estimated.

Together, (9) and (10) imply that the survivor function can be rewritten as

$$S(t, X) = \left[ - \int_0^t \theta_0(t)\lambda du \right] = \exp \left[ -\lambda \int_0^t \theta_0(t) du \right] = \exp[-\lambda H_t]$$

(11)

where $H_t$ is the integrated baseline hazard function evaluated at the end of the interval and therefore the baseline survivor function can be written as

$$S_0(t) = \exp[-H_t]$$

(12)

The discrete time hazard function (the probability of exit in interval $t$, conditional on surviving up to the beginning of interval $t$) is given by
\[
h(t, X) = \frac{S(t - 1, X) - S(t, X)}{S(t - 1, X)} = 1 - \frac{S(t, X)}{S(t - 1, X)} = 1 - \exp[\lambda(H_{t-1} - H_t)] \tag{13}
\]

which implies

\[
\log(1 - h(t, X)) = [\lambda(H_{t-1} - H_t)] \tag{14}
\]

and thus,

\[
\log(-\log[1 - h(t, X)]) = \beta X + \log(H_{t-1} - H_t) \tag{15}
\]

The discrete baseline hazard for the \( t^{th} \) interval can be written as

\[
1 - h_0(t) = \exp(H_{t-1} - H_t) \tag{16}
\]

and hence,

\[
\log(-\log[1 - h_0(t)]) = \log(H_{t-1} - H_t) = \log\left[ \int_{t-1}^{t} \theta_0(u)du \right] = \gamma(t) \tag{17}
\]

where \( \gamma(t) \) is the log of the difference between the integrated baseline hazard function evaluated at the end and the beginning of the time interval.

Together, (15) and (17) give the discrete time hazard rate function:

\[
\log(-\log[1 - h(t, X)]) = \beta X + \gamma(t) \tag{18}
\]

This transformation is known as the complementary log-logistic transformation and the discrete time proportional hazards model in (18) is often referred as a random effects cloglog model.
If each interval is of unit length, the hazard function can be finally rewritten as

$$h(t, X) = 1 - \exp[-\exp(\beta X + \gamma(t))]$$

(19)

The cloglog model is a generalization of the linear model with a particular link function $\gamma(t)$. This link function summarizes the pattern of time dependence in the interval hazard (Jenkins, 2005).
5. Results

We performed a continuous time duration analysis to understand the determinants of firm survival. First, a series of regressions were run, adding the variables sequentially. Pre-entry experience is captured by the five categories’ dummy and other variables are added as controls. The model reports the results considering exit, both by liquidation and acquisition. In our sample half of the exits occurred by acquisition and half by liquidation. Existing empirical findings suggest that important differences exist between exit by liquidation and exit by acquisition (Schary, 1991). However, investigating the reason of acquisitions is not the goal of this thesis.

Moreover, we performed a robustness check of the findings with a discrete time duration analysis, using different baseline hazard functions.

Finally, to understand the factors affecting the innovativeness of our sample, we carried out a logit regressions using patent filing as dependent variable.

5.1 Preliminary Results

Our results using the Cox proportional hazard model are reported in Table 8, where the first six models are presented and the variables are added progressively. A hazard ratio of one indicates that the corresponding variable has no effect on the baseline hazard. A coefficient less than one indicates that an increase in the value of the variable lowers the hazard of exit. A coefficient greater than one indicates that an increase in the value of the variable raises the hazard.

Model (1) tests the hypothesis that pre-entry working experience of the founders affects the survival of the start-ups. The variable is categorical, then we have to explain the result with respect to the base category, which is inexperienced start-ups. Consistently with the previous literature (Fontana and Malerba, 2010; Adams, Fontana and Malerba, 2012), the coefficients estimates for university start-ups and spin-offs are lower than inexperienced firms. This result is significant and robust to the inclusion of additional explanatory variables. This implies that these two
groups of experienced firms survive relatively longer than the base category, suggesting that pre-entry experience is a key determinant of success.

The results for demand spin-offs are significant only in Model (4) and (6), but they anyhow suggest that for new firms in the ICT industry with previous experience in downstream sectors it is easier to survive.

In addition, mixed start-ups do not seem to have a significant different hazard rate compared to inexperienced start-ups and other categories of entry.

After having analyzed the impact of pre-entry experience, in the remaining models we studied the effect of some control variables that should be related with firm survival.

In Model (2) the variable serial entrepreneur was included in order to check if the prior business experience of the founders affects the performance of new firms. In the estimated models this variable is not significant, suggesting that is not affecting survival performance of new entries.

In Model (3) we controlled for venture capital support, in particular Venture Leaders and Venture Lead programs, since previous studies have underlined that VC support is an important determinant of firms’ survival, but the results are not significant.

Model (4) controls for university affiliation, but also in this case the coefficients are not significant and thus we are not able to give a clear indication.

To check whether the number of founders affects the survival of new firms, in Model (5) we included the variable founded by team. The coefficients are always significant at a 5% confidence level and lower than one, indicating that team of founders could benefit from sharing different skills and capabilities. This result is in line with previous studies that found firms created by a team have a lower hazard rate (Cooper and Bruno, 1977).

Finally, in Model (6) we inquired the relationship between innovativeness and survival of new firms. The dummy considers firms who patented at the European Patent Office or at the US Patent and Trademark Office, but the coefficient is not significant and no clear indication can be derived.
All in all, the preliminary results presented above support the hypothesis that pre-entry work experience of the founders is a key determinant of firm survival. In particular, spin-offs, demand spin-offs, and university start-ups showed a relatively lower hazard rate compared to inexperienced firms, confirming the previous literature. The analysis pointed out, also, that controlling for human capital characteristics, multiple founders teams positively affect firms’ performance.

Table 8 – Cox Proportional Hazard Model

<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>University Start-ups</td>
<td>0.373</td>
<td>0.391</td>
<td>0.381</td>
<td>0.258</td>
<td>0.318</td>
<td>0.299</td>
</tr>
<tr>
<td></td>
<td>(0.200)</td>
<td>(0.209)</td>
<td>(0.205)</td>
<td>(0.163)</td>
<td>(0.204)</td>
<td>(0.192)</td>
</tr>
<tr>
<td>Spin-offs</td>
<td>0.334</td>
<td>0.328</td>
<td>0.325</td>
<td>0.321</td>
<td>0.300</td>
<td>0.290</td>
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<tr>
<td></td>
<td>(0.171)</td>
<td>(0.168)</td>
<td>(0.166)</td>
<td>(0.176)</td>
<td>(0.165)</td>
<td>(0.160)</td>
</tr>
<tr>
<td>Demand Spin-offs</td>
<td>0.281</td>
<td>0.274</td>
<td>0.278</td>
<td>0.248</td>
<td>0.275</td>
<td>0.223</td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
<td>(0.218)</td>
<td>(0.221)</td>
<td>(0.206)</td>
<td>(0.229)</td>
<td>(0.196)</td>
</tr>
<tr>
<td>Mixed Start-ups</td>
<td>0.443</td>
<td>0.452</td>
<td>0.442</td>
<td>0.405</td>
<td>0.607</td>
<td>0.626</td>
</tr>
<tr>
<td></td>
<td>(0.276)</td>
<td>(0.281)</td>
<td>(0.275)</td>
<td>(0.268)</td>
<td>(0.431)</td>
<td>(0.446)</td>
</tr>
<tr>
<td>Serial Entrepreneur</td>
<td>1.474</td>
<td>1.441</td>
<td>1.283</td>
<td>1.471</td>
<td>1.522</td>
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<tr>
<td></td>
<td>(0.546)</td>
<td>(0.536)</td>
<td>(0.509)</td>
<td>(0.595)</td>
<td>(0.623)</td>
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<tr>
<td>VC support (Leaders or Lab)</td>
<td>0.677</td>
<td>0.501</td>
<td>0.478</td>
<td>0.474</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.341)</td>
<td>(0.289)</td>
<td>(0.280)</td>
<td>(0.278)</td>
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</tr>
<tr>
<td>University Affiliation</td>
<td>1.805</td>
<td>1.880</td>
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</tr>
<tr>
<td></td>
<td>(0.812)</td>
<td>(0.845)</td>
<td>(0.915)</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Founded by team</td>
<td>0.362</td>
<td>0.333</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.165)</td>
<td>(0.157)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPO and USPTO Patent</td>
<td></td>
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<td>1.072</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0630)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>259</td>
<td>259</td>
<td>250</td>
<td>250</td>
<td>250</td>
</tr>
</tbody>
</table>

Exponentiated coefficients; Standard errors in parentheses
\(^{\ast}p < 0.1, \quad ^{\ast\ast}p < 0.05, \quad ^{***}p < 0.01\)
5.2. Robustness Check

To check the robustness of our findings we performed a discrete time duration analysis. The original dataset counting 259 firms was expanded to 16,041 observations and several baseline hazard functions (logarithmic, polynomial, and Weibull with q equal to 0.5 and 1.5) have been tested. Results of the regressions are reported in Table 9.

In the four specifications presented we used the same variables accounted for the Cox proportional hazard model, in order to compare the two models with the same determinants.

The results are significant and consistent with the Cox model results, with similar coefficients for all the variables taken into account. University start-ups, spin-offs, and demand spin-offs experience respectively only 30%, 28%, and 22% of the risk of failure faced by inexperienced start-ups, confirming the importance of pre-entry knowledge. The hazard rate associated with demand Spin-offs in the discrete time model turns out to be more significant than in the continuous case.

The dummy variable for multiple founders team is still significant at 5% level, indicating that firms founded by more than one founder face around 35% of the risk of failure experienced by those founded by a single founder.

As for the Cox models, the other variables such as mixed start-ups, serial entrepreneur, VC support, university affiliation, and patents activity are still not significant, but the values are consistent with the original model.
Table 9 – C-loglog Discrete Time Estimates with alternative specifications

<table>
<thead>
<tr>
<th></th>
<th>(1) ln(j)</th>
<th>(2) Polynomial</th>
<th>(3) Weibull 0.5</th>
<th>(4) Weibull 1.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>University Start-ups</td>
<td>0.308*</td>
<td>0.309*</td>
<td>0.308*</td>
<td>0.308*</td>
</tr>
<tr>
<td></td>
<td>(0.197)</td>
<td>(0.198)</td>
<td>(0.197)</td>
<td>(0.197)</td>
</tr>
<tr>
<td>Spin-offs</td>
<td>0.287**</td>
<td>0.288**</td>
<td>0.287**</td>
<td>0.287**</td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.158)</td>
<td>(0.157)</td>
<td>(0.157)</td>
</tr>
<tr>
<td>Demand Spin-offs</td>
<td>0.225*</td>
<td>0.226*</td>
<td>0.225*</td>
<td>0.225*</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.200)</td>
<td>(0.199)</td>
<td>(0.199)</td>
</tr>
<tr>
<td>Mixed Start-ups</td>
<td>0.627</td>
<td>0.639</td>
<td>0.627</td>
<td>0.627</td>
</tr>
<tr>
<td></td>
<td>(0.446)</td>
<td>(0.455)</td>
<td>(0.446)</td>
<td>(0.446)</td>
</tr>
<tr>
<td>Serial Entrepreneur</td>
<td>1.632</td>
<td>1.636</td>
<td>1.632</td>
<td>1.632</td>
</tr>
<tr>
<td></td>
<td>(0.667)</td>
<td>(0.668)</td>
<td>(0.667)</td>
<td>(0.667)</td>
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<tr>
<td>VC support (Leaders or Lab)</td>
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<td>0.476</td>
<td>0.476</td>
<td>0.476</td>
</tr>
<tr>
<td></td>
<td>(0.279)</td>
<td>(0.279)</td>
<td>(0.279)</td>
<td>(0.279)</td>
</tr>
<tr>
<td>University Affiliation</td>
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<td>2.015</td>
<td>2.004</td>
<td>2.004</td>
</tr>
<tr>
<td></td>
<td>(0.907)</td>
<td>(0.910)</td>
<td>(0.907)</td>
<td>(0.907)</td>
</tr>
<tr>
<td>Founded by team</td>
<td>0.357**</td>
<td>0.347**</td>
<td>0.357**</td>
<td>0.357**</td>
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<tr>
<td></td>
<td>(0.167)</td>
<td>(0.165)</td>
<td>(0.167)</td>
<td>(0.167)</td>
</tr>
<tr>
<td>EPO and USPTO Patent</td>
<td>1.079</td>
<td>1.081</td>
<td>1.079</td>
<td>1.079</td>
</tr>
<tr>
<td></td>
<td>(0.0631)</td>
<td>(0.0637)</td>
<td>(0.0631)</td>
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<tr>
<td>j</td>
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<tr>
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</tr>
<tr>
<td>j2</td>
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</tr>
<tr>
<td>j3</td>
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<td>ln(j)</td>
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<td>(0.977)</td>
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<tr>
<td>Weibull 0.5</td>
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<td>0.103***</td>
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<tr>
<td></td>
<td></td>
<td>(0.0650)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weibull 1.5</td>
<td></td>
<td></td>
<td>9.663***</td>
<td></td>
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<tr>
<td></td>
<td></td>
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<td>(6.071)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>16,041</td>
<td>16,041</td>
<td>16,041</td>
<td>16,041</td>
</tr>
</tbody>
</table>

Exponentiated coefficients; Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01
5.3. Further Results

The previous sections have showed how working experiences and the composition of founding teams affect the performance of new firms in the Swiss ICT industry. However, the survival of a new entrant is not always related to the success of the company. The degree of innovativeness is also important to measure the overall performance of a firm.

Therefore, we decided to focus also on the factors that affect the propensity to grant a patent, both at the European Patent Office and at the US Patent and Trademark Office.

For the purpose of this analysis we performed a Logit model using as dependent variable a dummy that assumes the value one if the firm has granted a new patent either at the EPO or at the USPTO. In order to control for firms’ age we grouped the sample in three cohorts: firms born between 2000 and 2005, firms born between 2006 and 2009, and firms born after 2009. The results of the regressions are reported in Table 10.

In Model (1) we added the categorical variable related to pre-entry working experience of the founders, considering the inexperienced start-ups as base category. Coefficients for mixed start-ups are positive and significant, showing that firms with founders having different professional backgrounds are more innovative and thus more likely to file a patent than inexperienced firms. This is an important conclusion because we didn’t find evidence of better performances in the previous models based on survival period. Instead, in relation to innovativeness, mixed start-ups are outperforming the others categories. We assume that since they bring together different competences they are more likely to adopt an exploratory behavior instead of an exploitative one (Bechman, 2006), coming up with innovation that is worth patenting. Also university start-ups are found to be significant and positive in the last model, suggesting that founders coming from the university environment are more likely to patent than inexperienced start-ups.

In order to catch the effect of VC support on patent propensity, in Model (2) we included two dummies for firms that participated to Venture Leaders and Venture Lab programs. The results for Venture Leaders are positive, significant, and robust,
suggesting that benefit from VC has a positive influence on the probability to file a patent. This is consistent with Kortum and Lerner (2000), who found that VC backed firms produce more patents than other new ventures, and this is linked with the selection process that they have to face to receive the support. On the other side, Venture Lab support showed negative coefficients, but are never found to be significant.

In Model (3) and (4) controls to evaluate the effect of serial entrepreneurship and the presence of multiple founders teams were added, but the results are not significant.

Moreover, a variable for firms with at least one founder that has an educational background related to the industry (e.g. Engineering, Computer Science), and a variable for firms with universities affiliation has been included in Model (5). Interestingly, coefficients for ICT-related educational field are positive and significant, suggesting that the educational level and specialization of the founders of a start-up is positively related to the probability of granting a patent in the ICT industry.

Finally, in Model (6) we included a control variable to check if firms with founders coming from the same previous company are more innovative than others, but the coefficient is not significant thus we are not able to derive a clear indication. The idea was to test the hypothesis that teams of founders left the previous company because already had a new idea to develop and should have been more inclined to patent a new product. Future research on this topic could focus also on the time to patenting to verify this hypothesis. The final Model (6) has a Pseudo $R^2$ equal to 0.34.

Of course in this analysis we have only preliminary tested the aspect of innovativeness, by distinguishing between firms who patent and firms who don't. Additionally, not all the patents are of equal relevance and citations analysis could help to optimize the results. However, patenting is just one aspect of innovative activity, and other output as product and process innovation should be taken into consideration in future research.
Table 10 – Logit Model for EPO or USPTO Patent

<table>
<thead>
<tr>
<th></th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
<th>Model (4)</th>
<th>Model (5)</th>
<th>Model (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>University Start-ups</td>
<td>0.491</td>
<td>1.636</td>
<td>1.635</td>
<td>2.150</td>
<td>2.062</td>
<td>3.006*</td>
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<td></td>
<td>(0.767)</td>
<td>(1.232)</td>
<td>(1.233)</td>
<td>(1.339)</td>
<td>(1.427)</td>
<td>(1.766)</td>
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<tr>
<td>Spin-offs</td>
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<td>1.047</td>
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<td>0.561</td>
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<td>(0.715)</td>
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<td>(1.241)</td>
<td>(1.298)</td>
<td>(1.303)</td>
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<td>0.409</td>
<td>0.353</td>
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<td></td>
<td>(0.965)</td>
<td>(1.521)</td>
<td>(1.523)</td>
<td>(1.608)</td>
<td>(1.573)</td>
<td>(1.597)</td>
</tr>
<tr>
<td>Mixed Start-ups</td>
<td>0.709</td>
<td>2.113*</td>
<td>2.111*</td>
<td>2.861**</td>
<td>2.550*</td>
<td>2.801*</td>
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<td>(1.191)</td>
<td>(1.373)</td>
<td>(1.410)</td>
<td>(1.456)</td>
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<td>VC Support (Leaders)</td>
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<td>1.781**</td>
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<td>1.926*</td>
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<td>(0.905)</td>
<td>(0.910)</td>
<td>(1.050)</td>
<td>(1.122)</td>
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<td>VC Support (Lab)</td>
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<td>(0.740)</td>
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<td>Founded by team</td>
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</tr>
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<tr>
<td>Edu field related</td>
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<td>2.408*</td>
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<tr>
<td></td>
<td>(1.110)</td>
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<td>(1.239)</td>
<td>(1.252)</td>
<td>(1.307)</td>
<td>(1.652)</td>
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<td>Observations</td>
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</table>

Standard errors in parentheses

* p < 0.1,  ** p < 0.05,  *** p < 0.01
6. Conclusions and Limitations

This thesis has examined the entry and survival of new firms in the Swiss ICT industry. Creating a dataset of 259 start-ups founded between 2000 and 2013, we investigated the relationship between firms background and survival. The main focus was given to pre-entry experience of the founders and firms’ hazard rate, but different human capital characteristics, financing, and innovativeness have been considered as well.

Our results indicate that experienced start-ups have a lower hazard rate than inexperienced start-ups. This is due to their specific technological, market, application, or organizational knowledge (Adams, Fontana, and Malerba, 2013). In particular, spin-offs (firms with experience in the ICT industry) are among the best performers. This result confirms recent findings in high-tech industries. Additionally, confirming the findings of Fontana and Malerba (2010) on Semiconductor industry, an interesting result is that firms coming from the demand side (demand spin-offs) have slightly lower hazard rate not just with respect to inexperienced firms, but also to university start-ups and classic spin-offs. Growing involvement of users in the process of innovation, knowledge about applications, and high heterogeneity of applications, could be among the determinants of this outperformance.

Second, our findings indicate that the characteristics of the founding team affect the probability of survive. In fact, new firms founded by a team are more likely to survive than those who have been founded by a single founder. This is consistent with previous literature that showed larger founding teams sharing more skills and capabilities and thus having generally a lower hazard rate (Cooper and Bruno, 1977; Roberts, 1991).

Third, since start-ups that survive longer are not necessarily more innovative than other start-ups, our analysis stressed also the importance of innovativeness in order to check the previous results. Dividing the sample among firms who patent and firms who do not, we found that the best performers are mixed start-ups (firms founded by a team coming from different working background).
Lastly, VC backed firms and start-ups with founders having educational studies related to ICT business enjoy a higher probability to hold patents compared to the others.

In conclusion, this study contributes to the literature that focused on the relationship between entry and industrial dynamics, by providing insight into how the characteristics of the knowledge of founding teams of de novo entrants affects the performance of their firms.

However, several limitations of the study may be observed due to the assumptions made and the restricted information available. Their identification may provide useful suggestions for future research.

First, it is not possible to generalize our findings, that holds for a specific industry (ICT) within a specific time frame (2000-2013), and future studies should investigate the extent to which they hold in different industries and periods.

Second, classification of firms into categories based on pre-entry experience of their founders requires some assumptions. Effort has been made to avoid biases in the classification, but still a certain degree of arbitrariness may exists.

In addition, we based our classification on the background of founders, excluding the possibility that other employees of the companies could make the difference. Of course, this was the most reasonable choice for a sample of many firms but in future research, it would be interesting to consider also previous experiences of other employees.

Moreover, we focused on the last working experience of founders, in order to have a common base of reference, but future studies could investigate the entire professional background of founders to enrich the classification.

A further limitation of this research concerns our data on survival and exit. We were not able to trace the history of firms that exited the industry after the time considered and we do not distinguished in our models between exits by liquidation and exits by acquisitions. It is a topic worth discussing, indeed, since acquisitions could be seen as a signal of success rather than failure.

Additionally, only survival period has been considered as a measure for performance, while other indicators such as growth rate, sales, profitability, and
market share have not been considered due to the lack of information. In fact, despite the assumption that survival is linked with good performance, there is evidence that some underperforming firms persist in the market, whereas voluntary exit can occur without economic failure (Gimeno et al., 1997).

As far as innovativeness is concerned, patent granting is just one aspect of innovative activity and we should also be able to account for product or process innovation activity, as well as R&D performance.

Finally, results have been obtained from a relatively small sample of firms active in a specific country; it would be worth conducting the same analysis in other geographical contexts with a larger sample.

All these issues represent steps that could be addressed by future studies.

7. Acknowledgments

I am grateful to my supervisor, Professor Valentina Tartari for her support on this project and her valuable comments and suggestions on previous drafts that provided excellent research assistance. I also thank my father Tiziano, my brother Alessio, and my girlfriend Babi, because without their support it wouldn’t be possible for me to reach this goal. In addition, thanks to all my friends I met during my unforgettable experience in Copenhagen. Finally, I dedicate this thesis to my mother Clotilde, I miss you!
8. References


Cooper, A.C. (1986). Entrepreneurship and High


9. Appendix

Figure 2 – Entry and Exit time distribution
Table 5 – Geographical Distribution

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<tr>
<th>Canton</th>
<th>N. of Entry</th>
<th>% of Entry</th>
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<td>4,2%</td>
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<tr>
<td>Zug</td>
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<tr>
<td>Fribourg</td>
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<tr>
<td><strong>Total</strong></td>
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