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Three Essays on the Human and Social Capital Effects and Entrepreneurial Firm Performance

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THREE ESSAYS ON THE HUMAN AND SOCIAL CAPITAL EFFECTS AND ENTREPRENEURIAL FIRM PERFORMANCE

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ABSTRACT

This dissertation contains three articles that focus on several ways to measure human and social capital and their links to different entrepreneurial outcomes. The study begins by providing an overview of entrepreneurship policy research, highlighting the need for an interdisciplinary approach in this subfield of policy analysis. In the first article, human capital theory is used to understand variations in innovative behavior depending on the size of manufacturing companies in a developing economy. In the second article, factors associated with entrepreneurs' cumulative advantages in the financial systems(s) were identified by applying a novel statistical modeling strategy from the field of entrepreneurship research. In the third research article, an estimation of entrepreneurs' human capital impact on new venture performance is analyzed by applying a heterodoxic theory of human capital, widely used in entrepreneurship research at the regional level, but for the first time at the firm level. The dissertation concludes by providing a general discussion of the findings, policy implications, and potential further research avenues.

DEDICATION

I dedicate this dissertation to Victoria, my wife, for her unwavering support during these five years and, especially, for the happy years to come.

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I would like to express my gratitude to my dissertation chair, Professor Lori Dickes, for her continuous support during these five years at Clemson University. Her patience and encouragement guided me throughout the dissertation process. Good advisors help students to complete their dissertation, but mentors encourage you to achieve your goals far beyond it. Dr. Dickes fits this definition, and I am eternally grateful to her. Also, I would like to thank the members of my dissertation committee, Dr. Brook Russell, Dr. Chad Navis, and Dr. David Wyman, for their support, patience, encouragement, comments, and insights.

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Last but not least, to my family and friends in Uruguay, I always knew you would be there any time I needed you to support me. So, to my parents, Emilio and Mariella; my siblings Mateo, Julieta, and Lucas; my parents-in-law Baltasar and Doris; and my great friends Braulio, Daniel, José, and María; I will always be grateful to you all.

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CHAPTER ONE

INTRODUCTION

Several investigations have focused on the relationship between entrepreneurship and economic growth (Urbano, Aparicio, and Audretsch, 2018), using different theoretical frameworks and methodologies, finding a positive relationship between these factors, at the regional, national, and international level. Entrepreneurship is not only crucial for economic growth, but also new companies have an essential role in the creation of employment and innovation as well. For example, Birch (1979) found that companies with few than 100 employees generated 82% of the net gain of employment in the U.S. economy between 1969 and 1976. In addition, in investigating leading European economies, Storey and Johnson (1987) found that employment net generation in small and medium enterprises was higher compared to large companies. Timmons (1994) discovered that new ventures generated 50% of innovations in processes and 95% of the radical innovations in the U.S. economy during the last years of the 80s. Acs and Armington (2004) estimated that new firms create between 20-50 % of net new jobs and almost all net jobs during the first years of the 21st century.

Entrepreneurship research emerged to provide information on how to foster these economic development aspects. This research field explores questions about who, where, how, and why individuals initiate, expand, and close their business. Since individuals do this for a wide variety of reasons, ranging from economic to psychological ones, this domain of knowledge is an interdisciplinary research field. Therefore, entrepreneurship scholars come from a range of backgrounds, from management science, economics, sociology, or anthropology, and policy analysis, to mention a few.

This dissertation aims to focus on the latter by suggesting policy recommendations. However, historically and currently, the transformation of entrepreneurship research into policy recommendations is not simple and straightforward. The development of entrepreneurship policy was developed pragmatically by trial and error rather than beginning from an ex-ante and well-defined theoretical approach (Hart, 2003). Probably, the interdisciplinary nature of the field of entrepreneurship research played a role in delaying a precise translation of the research findings into policy recommendations. Consequently, the researcher needs to become involved in a broad range of research fields and approaches to understand the entrepreneurial phenomena before suggesting precise policy recommendations.

Specifically, this dissertation contributes to the field of entrepreneurship policy by providing empirical findings on the relationship between the accumulation of assets that individuals can acquire and entrepreneurship. The three research articles of this dissertation use several outcomes such as product innovation, external funding, the creation and survival of new companies, and new job creation. The series of articles draws insight from various disciplines, primarily economics, but also regional and management studies, sociology, psychology, and public policy, allowing for a comprehensive perspective for policymakers in addressing issues regarding entrepreneurial development. It also applies a broad set of statistical techniques.

The cutting-edge advantage of the articles presented in this research is the scope of the analysis they share: the firm level. Several policy recommendations in the field of entrepreneurship research are derived from aggregated data, either from companies or from individual entrepreneurs. In this sense, mainstream Economics often treat the companies as black boxes that use inputs in and create outputs. This treatment of companies could lead to misleading policy recommendations, especially for entrepreneurship policy, since nascent ventures are more fragile as they first attempt to become operative compared to already operating established firms. For this reason, a deep understanding of the characteristics of nascent enterprises and entrepreneurs is useful for detecting critical factors for this type of business. This research opens the black box of new ventures and companies. In addition, analyzing firm-level' data has the advantage of contextualizing understanding of a firm's operativeness. In small and less developed economies, such as those examined in the first article, firms operate far from the technological frontier, applying out of date methods of production. If the firm level is not considered, an imprecise picture of new ventures and the companies of the developing world will result from the analysis, leading to ineffective policy recommendations. The second and third articles analyze new ventures by investigating factors at the new venture level, from the initial steps of the nascent entrepreneurs to set up a company until its creation or disengagement, allowing for a thorough picture of the factors that foster or inhibits the entrepreneurial process.

Theoretically speaking, this dissertation innovates in several ways. In this first paper, the human capital theory is applied to explore its relationship with innovation outcomes in the context of a developing economy. As is explained in this article, only limited research conducted similar studies for the Latin American region and none for Uruguay specifically. The second article applied the sociological Matthew effect theory of cumulated advantages for the first time to investigate entrepreneurial financing. Third, the theory of the creative class, which has been used extensively over the last two decades to understand entrepreneurship outcomes at the regional level, was applied at the firm level for the first time as well.

More specifically, the data source used in the first research article is a unique panel dataset for the Uruguayan economy. The Uruguayan Innovation Survey (UIS) is a triennial project that surveys industrial data. Its creation followed the international recommendations based on the

Bogotá Manual (RICYT, 2001), an adaptation of the Oslo Manual (OECD, 1992) to Latin America, to capture a firm's technological behavior. The National Agency for Research and Innovation of Uruguay collects this data from Uruguay on a triennial base. I collaborated with the Instituto de Economía, Universidad de la República in Uruguay, which was the research organization that combined all the UIS available created the panel dataset as a result. This panel dataset combines four triennial industrial surveys, making it the best source to investigate the research topic.

The Panel Study of Entrepreneurial Dynamics (PSED) is the data source used for the second and third articles. The PSED contains data from individuals engaged in the start-up process, and by applying follow-up interviews, it tracks the entrepreneur's progress as they move toward the creation of a profitable new venture. The two datasets, PSED-I and PSED-II represent two cohorts, one started in 1999 and the second in 2005. These datasets were combined, using the PSED harmonized transition dataset (Reynolds and Curtin, 2011). As Shim and Davidsson (2018) argued, using the PSED projects combined with the harmonized transition PSED is arguably the best available resource for assessing the duration of venture creation processes since PSED sample is based on a random sampling of individuals attempting to start a company in the U.S. PSED reduces to the minimum the biases associated with recalling the past activities. In other datasets available, the respondent entrepreneurs have to recall the initial steps and activities taken to create their company, resulting in the so-called recall-bias. PSED offers the advantage of tracking entrepreneurs during the entrepreneurial process from the very beginning, reducing this bias. Also, it allows for reducing the overestimation of successful ventures over those that stop their operations, since PSED surveys individuals regardless of the future of their new venture projects.

Often, business datasets include only operating firms at the time of the survey, overestimating successful firms.

The structure of this dissertation is as follows. The first article focuses on the relationship between human capital and entrepreneurship development in the context of Uruguay, a Latin American economy that developed a broad set of policies towards improving its innovation levels in the manufacturing industry through human capital. This research found that while the vast majority of these policies focused on targeting the improvement of the formal education of employees, not all dimensions of human capital impact innovation positively and in the same direction for all types of companies, similar to results found for other developing economies (Nazarov and Akhmedjonov, 2012; De Winne and Sels, 2010). This research calls for precise policies that target specific companies and their critical human capital assets to foster positively their innovation levels.

The second article focuses on the relationship between a broad set of entrepreneurial assets, ranging from wealth to social capital, and their impact on receiving external funding in the U.S. context. Receiving external funding has found to be a critical factor of entrepreneurial success (Hechavarría, Matthews, and Reynolds, 2016; Gartner, Frid, and Alexander, 2012). This article extends from the Matthew effect theory (Merton, 1968), which explains why initial advantages lead to further cumulative advantages. The original development of this theory aimed to explain the scientific reward system. Scientists with more recognition in their fields are usually funded, while conversely, less well-known scientists are less likely to be rewarded for their contributions.

More specifically, this article investigated if some factors associated with an entrepreneur's primary advantages also impact the further advantages of receiving external funding. This hypothesis extends on previous research that has shown an unbalance external funding awarded to wealthier entrepreneurs (Gartner, Frid, and Alexander, 2012; Frid, Wyman, Gartner, and Hechavarria, 2016; Frid, Wyman, and Coffey, 2016). Since some entrepreneurs are funded several times during their initial actions to set up a company while others never obtain external funding, this research applied a novel statistical modeling strategy for entrepreneurship research that takes into account the repetitive nature of receiving funding. The findings from this research emphasize that receiving funding several times is a critical factor for new startup creation and survival. They also challenge previous findings associated with the reception of external funding that did not consider the repetitive nature of this event. As a result, the article highlights a potential Matthew effect occurring in entrepreneurship funding.

Lastly, the third article investigates the performance of nascent startups led by entrepreneurs exhibiting a specific human capital asset, creativity. Based on the theory of the Creative Class (Florida, 2002), which has had a considerable influence on regional studies and economic geography, this theory questions the mainstream approach toward the relationship between entrepreneurship and human capital, which aims to measure the latter through the knowledge that people possess using educational attainment and other related variables. The Creative Class approach suggests an alternative way of measuring human capital based on an individual's occupation. While the Creative Class has been found to be more precise than the classical approach to human capital for several entrepreneurship outcomes at the regional level, this theory has never been applied and tested at the firm level. Given the significant evidence of the relationship between the Creative Class measurements and regional entrepreneurship, this third article focuses on the entrepreneurial teams and investigates the relationship between the number of creative owners and their startup performance. The findings from this article highlight the superior levels in employment creation and firm survival for those teams composed of creative entrepreneurs, defined as those who had a creative occupation before transitioning to entrepreneurship. The findings also provide insights on how to improve human capital measurement at the firm level, showing that as well as in regional studies, creative class variables outperform the classical human capital variables that measure educational attainment for several outcomes explored.

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CHAPTER TWO

HUMAN CAPITAL AND INNOVATION IN URUGUAYAN MANUFACTURING FIRMS

1-INTRODUCTION

The determinants of innovation at the country level are worth investigating since it is a critical component of economic growth (Romer, 1990; Solow, 1956; Schumpeter, 1934). At the country level, firms are the primary producers of innovations, and because it is a knowledge-based activity (Quintane, Casselman, Reiche, and Nylund, 2011) understanding how these agents acquire, update, and manage the knowledge of its employees is a crucial factor for economic growth. Thus, examining the relationship between human capital and innovation at the firm level is a critical component of entrepreneurship in a nation and for understanding the gap between developed and developing countries (Verspagen, 1993). To explore this phenomenon, this research investigates the role of human capital at the firm-level in the case of a small developing economy, specifically Uruguay. In the Latin American region, paradoxically, this country ranks among the top on several human capital dimensions. However, its manufacturing industry exhibits decreasing levels in incorporating human capital elements such as educated workers or internal training (ANII, 2015; Bianchi, Gras, and Sutz, 2011; Bianchi and Gras, 2003).

The effect of several human capital dimensions on firm product innovation is estimated by applying binomial logistic regression models with firm and time fixed effects. We consider three aspects of human capital. The first is the human capital endowments of firms, measured in this research by the number of employees holding a college degree. Second, we use two firm-level practices that impact on firm's human capital levels: internal training, and an index accounting for a relational-based management approach in manufacturing companies. The data used here come from a unique dataset created by merging triennial innovation surveys from the Uruguayan National Agency for Research and Innovation, covering from the period 2004-2006 to 2013-2015.

Based on these resulting estimations, this article made several contributions to the field. The most important is that not all dimensions of human capital operate in the same way for all companies. Individual endowments have a more significant impact on small firms, while firm-level practices such as internal training are a more critical factor for large companies. These findings suggest that the policy strategy followed by Uruguay should be reshaped by considering how human capital affects innovation depending on firms' size. While the policy approach to fostering innovation through human capital in the Uruguayan manufacturing industry currently relies primarily on increasing the educational level of employees, this approach can result in a negative impact on innovation for large firms.

2. PREVIOUS FINDINGS AND HYPOTHESES

2.1. Innovation studies in Uruguay

As innovation is a knowledge-based outcome (Quintane, Casselman, Reiche, and Nylund, 2011), how the agents acquire and manage knowledge is an essential factor for economic growth. Innovation requires a learning process, which is predominantly interactive and socially embedded (Arocena and Sutz, 2003; Lundvall, 2010). Therefore, the cultural context matters, and for that reason, examining the determinants of innovation at a particular cultural level such as a national context is essential for gaining a better understanding of innovation phenomena.

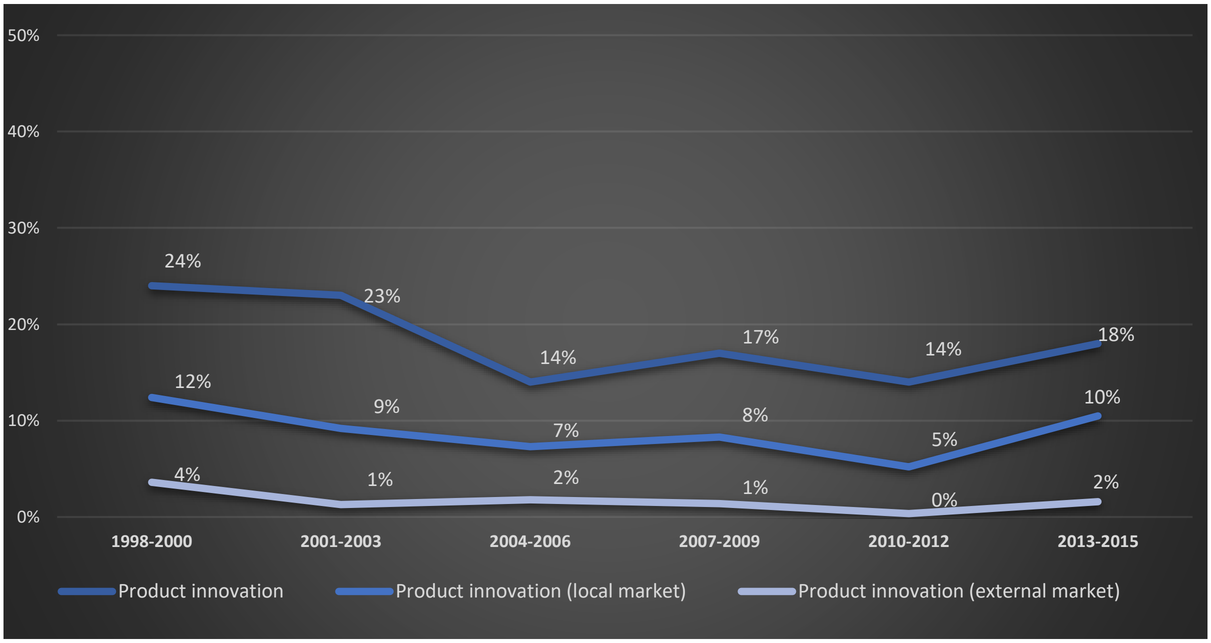
During the last two decades, innovation in developing countries has received increasing attention from scholars and policy-makers (Bartels, Voss, Lederer, and Bachtrog, 2012; The World Bank, 2010; Lundvall, Joseph, Camindade, and Vang, 2009). Firms in developing countries are particularly stimulating for innovation studies because the most important producers of innovations generally operate below the technological frontier. Through innovation, such as technology acquisition or imitation, firms in developing countries play a central role in reaching the global technological frontier.

This research focuses on one small developing economy such as Uruguay. This country has been a pioneer in innovation studies in the Latin American region. In 1985, the first empirical analysis of innovation activities conducted in the country (Argenti, Filgueira, and Sutz, 1988) and also the first in Latin America. In subsequent research, a handful of surveys provided information about the innovative behavior of the manufacturing industry, but not as a primary topic (Tansini and Triunfo, 1998a; 1998b). It was no until 1998 that the National Agency for Research and Innovation of Uruguay (ANII in Spanish acronym) conducted the first of six, systematic, and internationally standardized triennial surveys to understand the innovative behavior of the Uruguayan manufacturing industry[1]. These surveys are known as the Uruguayan Innovation Surveys (UIS).

Using UIS databases, researchers have highlighted stylized facts about the product and other innovation outcomes finding that innovation is a rare phenomenon in the Uruguayan manufacturing industry. In the UIS of 1998-2000, it was found that only 24% of the percentage of manufacturing firms that made one product innovation was. In 2002, a profound economic crisis occurred affected all economic sectors. In the UIS following the crisis in 2004-2006, only 14% of manufacturing firms introduced a product innovation.

[1] The last two surveys are not representative of the entire manufacturing industry. These surveys incorporated specific knowledge-intensive service activities to the sample.

Figure 1 – Percentage of manufacturing firms that introduced a product innovation 1998-2015



Source: UIS database, weighted. Own elaboration.

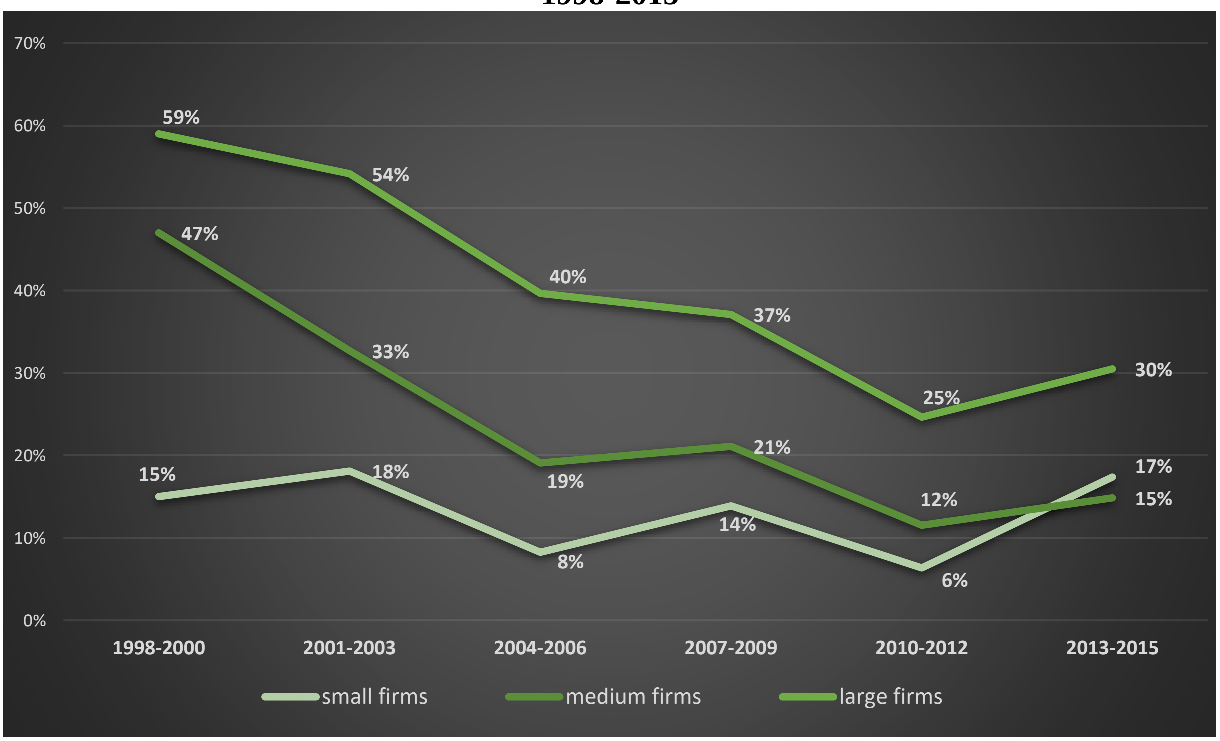
As a result of this crisis, the economic structure of the Uruguayan industry changed due to the exit of a significant number of manufacturing companies. Even today, the percentage of manufacturing firms that introduced a product innovation has never reached the levels before the 2002 economic crisis with less than 20% of manufacturing firms having achieved product innovation over the period of this study as Figure 1 shows. As this data suggests, innovation is still a rare phenomenon during Uruguay's ongoing economic recovery. Following the Bogotá manual (RICYT, 2001)[2], a firm can innovate at different levels; a product can be new to the firm itself, to the local market, or the external market. When we consider these two levels of innovation, the picture for the Uruguayan industry is even worse. Between 1998-2000, 12% and 4% of manufacturing introduced a new product for the local and the external market, respectively. After that year, there was a steady decrease in both levels of product innovation until conducted in 2010-

[2] The Bogotá Manual is an adaptation of the OECD's Oslo Manual to Latin-America that incorporates measurement tools and procedures to capture firms' technological behavior in this region, accounting for regional specificities. Further explanation can be found in section 4.

2012. Between 2013-2015, the number of firms that introduced a product innovation for the local market increased considerably from 5 to 10%.

From the last two decades, one definite conclusion of the research conducted in this field is that there is no clear pattern for innovation. However, some identifiable factors influence the innovative behavior of the Uruguayan manufacturing industry, standing out the size of companies. There is evidence that larger firms are more likely to innovate and to be innovative[3] (Bianchi, Lezama, and Peluffo, 2015; Cassoni and Ramada, 2010; Bianchi, 2007; Pittaluga, Llambí, and Lanzilotta, 2005; Argenti, Filgueira, and Sutz, 1988).

Figure 2 – Percentage of manufacturing firms that introduced a product innovation by size 1998-2015



Source: UIS database, weighted. Own elaboration. Note: Small firms represent those with 5-19 employees, medium-size 20-99 employees, and large-firms more than 99 employees

[3] Firms that have carried out innovation activities, but not necessarily achieved innovation results.

As Figure 2 shows, the picture is even worse when comparing firms by size, measured as 5-19 employees for small companies, 20-99 employees for medium firms, and large-firms with more than 99 employees. Although a slight recovery on the percentage of companies that introduced a product innovation in 2013-2015 occurred, this number decreased during the 1998-2015 period. In the case of large firms, 59% innovated in products in 1998-2000, dropping to 30% in 2013-2015. The mid-sized firms showed a similar trend from 45% in 1998-2000 to 15% in 2013-2015. The performance of small firms was more volatile in this regard, showing that 15% of companies in 1998-2000 could introduce a product innovation, and 17% of them did it in 2013-2015. Although in the last survey, small firms behave similarly to mid-sized firms, they were the least innovative regarding introducing new products, if the whole period is taken into account, as Figure 2 depicts.

Even though the firm size has been found to be a critical factor in innovation for developing countries, including Uruguay, many scholars emphasized another critical dimension which fosters innovation that was not investigated in depth: human capital assets. For example, following Becker's (1975) approach, education and training are seen as critical investments in human capital. In the author's perspective, the abilities, intelligence, and skills of employees acquired from formal education and job experience constitute an organization's human capital level. Scholars identified both factors as primary sources of innovation, and Uruguay has historically belonged to the group of countries with the highest levels of human capital in Latin America (Iván, Leonardo, Pérez-Fuentes, and Castillo-Loaiza, 2016). However, Uruguayan manufacturing firms have reduced both factors in the last years, as can be seen in Figures 3 and 4 in the next section. Perhaps, this reduction is linked to the weak innovation performance of the Uruguayan industry, suggesting that Uruguay is a compelling case to study the relationship between human capital and innovation.

2.1.1 Human capital and innovation: The Uruguayan context

As mentioned previously, Uruguay was a pioneer in developing innovation surveys in Latin America. In 1988, Argenti, Filgueira, and Sutz (1988) found that close to 75% of manufacturing companies between 20 and 49 employees did not have even one engineer in its staff. This percentage was similar when looking at the proportion of companies between 20 and 49 employees without a professional in their entire workforce.

Nevertheless, this early detection did not lead to a solution. During the first decade of the 21st century, this relationship still detected (Bianchi *et al.,* 2011). As it was pointed out by Bianchi *et al.* (2011), the proportion of firms that have professionals varies with their size; relatively smaller firms tend to hire fewer professionals. That trend became increasingly problematic: The reduction of professionals in small and medium firms is particularly dramatic and grew into a significant drawback during the last twenty years (Bittencourt, 2012). This negative relation between size and employee level of education has worsened during the period of this study.

The number of professionals is one of the proxies for a firm's knowledge absorptive capacity (Schmidt, 2010; Cohen and Levinthal, 1990). However, to assume the idea that increasing the number of professionals enhances a firm absorptive capacity implies that this relationship is linear. There is no reason to believe that hiring the 10th engineer for a 200-employee manufacturing firm will have the same effect as for a small 20-worker company that employs its first one does. For that reason, Argenti *et al.* (1988) address this issue, observing those firms that do not have any professional employees. As Figure 3 shows, the size of the firm and those having professionals and technicians are inversely related. It is also possible to note that the number of small manufacturing firms with no professionals grew over time, from 42.5 in 2004-2006 to 65.1 in 2013-2015. Similarly, mid-sized firms with no professionals in their workforce increased from

22.8 in 2004-2006 to 33.4 in 2013-2015. In the case of large firms, these percentage remained low and stable over the 2004-2015 period.

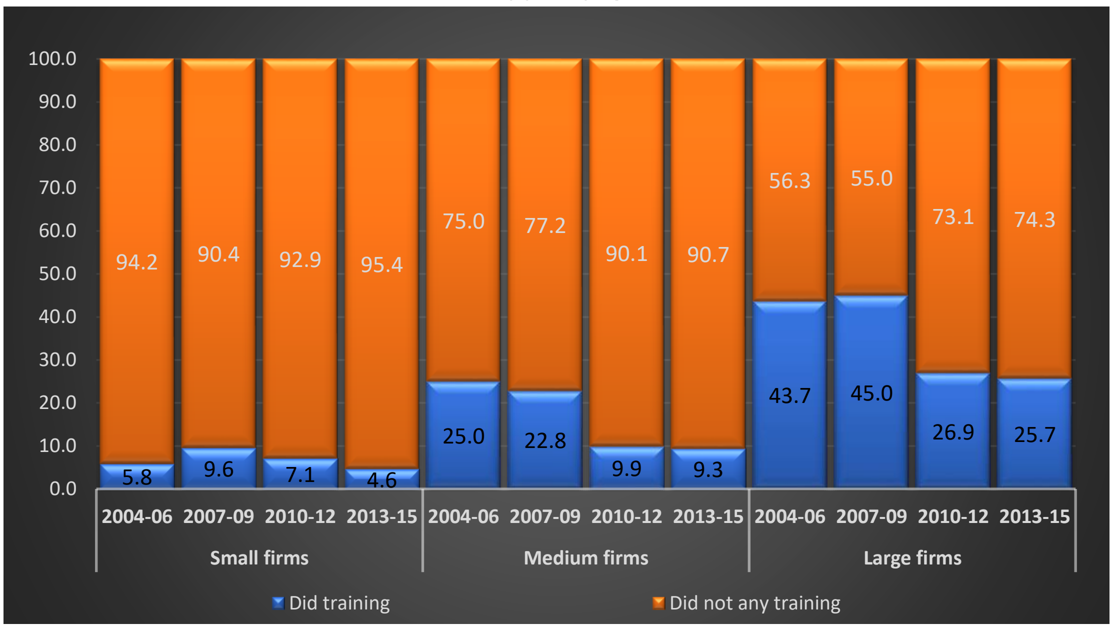
Figure 3 – Percentage of manufacturing firms that have at least a professional in its workforce or not, by size 2004-2015

Source: UIS database, own elaboration. Note: Small firms represent those with 5-19 employees, medium-size 20-99 employees, and large-firms more than 99 employees

Just as important as having skilled employees is maintaining their knowledge updated. Thus, internal training is another human capital asset. In this regard, again, the size of the firm is a critical factor. According to Cassoni and Ramada (2010), the role of a combined pool of innovative inputs (including training) is essential to increase the likelihood of innovation results in the Uruguayan industry. Through multiple correspondences and cluster analysis, Baptista (2015) identifies various business innovation patterns in Uruguay. She found that innovative high-tech firms represented only 6% of Uruguay productive structure. Almost 90% of these innovative firms employ professionals or technicians, and 60% develop internal training activities, investing significant financial resources in this area.

Figure 4 shows that the level of training varies with firms' size. Only between 5% and 10% of small firms provided internal training between 2004 and 2015, a percentage that increases for mid-sized firms to 25% in 2004-2006 but then slightly decreases to 9.3% in 2013-2015. In the case of large companies, 45% provided internal training in 2004-2006 but then also drops to 25.7% in 2013-2015. Summing up, the number of firms that pursues hiring professionals or did internal training was declining during the 2004-2015 for every size cohort.

Figure 4 – Percentage of manufacturing firms that did internal training or not, by size 2004-2015



Source: UIS database, own elaboration. Note: Small firms represent those with 5-19 employees, medium-size 20-99 employees, and large-firms more than 99 employees

Investigating how firms incorporate, manage, and update human capital is critical for recommending policies to foster innovation. These recommendations become even more important since the primary innovation input in the Uruguayan manufacturing industry has been the incorporation of "hard" innovative assets such as capital goods (ANII, 2015; Bittencourt, 2012) rather than "soft" ones such as hiring college-degree professionals, developing professional approaches of human resource management, or providing internal training (Bittencourt, Rodriguez, and Torres, 2009).

There is of importance to highlight the rise in the number of public policies aimed to promote firms' innovation through human capital during the last decade in Uruguay. In Appendix C depicts the objectives of these policies. However, in Uruguay and as well in other Latin American countries, such policies had limited success since they were formulated by imitating, mostly, developed countries' strategies. Through this policy-making approach, the local environment was not considered (Arocena and Sutz, 2010). An examination of the relationship between the firm's human capital and their innovation performance opens improvement opportunities for policymaking in this regard in Uruguay.

2.2. Human Capital and Innovation

Several studies have investigated the relationship between human capital and innovation at different levels, including individuals, organizations, and regions. This line of research focuses on the fact that humans possess skills that can be improved through education, training, and practice and can change how people behave (Pennings, Lee and van Witteloostuijn, 1998; Gimeno, Folta, Cooper, and Woo, 1997; Coleman, 1988; Becker, 1975). This paper focuses on the relationship between innovation and human capital at the firm level and results in that relationship are mixed; however, it is possible to find a clear division between studies that focused on either managers or employees. This paper focuses on the latter due to the lack of data exploring managers' human capital in the Uruguayan context.

Smith, Collins, and Clark (2005) investigated how the human capital of top management teams and production workers' affects innovation in the US. They found that the amount of education and its composition have a positive impact on the knowledge capabilities of large high-technology firms — the latter influences on their new products and services rates. Conversely, the often-cited research of Subramaniam and Youndt (2005) found that employees' human capital negatively impact on the innovative capabilities of large firms. This relationship, however, was moderated by social capital, implying that human capital only fosters innovation if it is networked, shared, and channeled through interrelationships within the firm. Nevertheless, in Spanish firms, according to Cabello-Medina, López-Cabrales, and Valle-Cabrera (2011), human capital exerts a direct influence on innovation and mediates the impact of social capital on it.

Other intangible assets influence the relationship between human capital and product innovation. In the study conducted by Costa, Fernández-Jardon Fernández, and Figueroa Dorrego (2014) on Portuguese firms, human capital impacts innovation only if their structural capital mediates it. Specific for the Taiwanese economy, Chen, Liu, Chu, and Hsiao (2014) found that human capital is positively related to customer capital, defined as the knowledge that allows firms to understand the preferences and latent needs of consumers, which in turn has a positive effect on new product development.

Most of these studies investigated the relationship between innovation and intellectual capital, for which human capital is a focal component, but in the context of developed economies. However, there is limited research focused on developing economies (Buenechea-Elberdin, 2017), where most of the firms are smaller and operate in low-tech sectors. This distinction is critical because there are key dimensions of human capital often not considered in developed economies that are important for understanding this relationship in the developing world. For example, Cabello-Medina *et al.* (2011) and Costa *et al*. (2014) considered training as one of their measurements of human capital, but neither Smith *et al.* (2005), Subramaniam and Youndt (2005) or Chen *et al.* (2014) did. Firm's internal training seems to be critical in the developing economies because the educational level of employees is one of the central innovation constraints in the developing world (George, Corbishley, Khayesi, Haas, and Tihanyi, 2016). Because in the context of a developing economy the lack of skilled workers is problematic, implementing internal training could be a strategy for addressing this issue. Thus, employees' educational level and internal training must be considered when focusing on developing countries, such as Uruguay. However, as the intellectual capital approach has found, intra-firm relationships could potentially influence innovation performance as well. For these reasons, these three dimensions are the focus of the research reported here.

2.2.1. Employees educational level and innovation

The number of educated employees in a firm is an indication of potential new ideas' development and transformation. Formal education helps organization members to improve their knowledge base, better predict outcomes, manage resources, and monitor results, meaning that it fosters the firm's learning process. For example, Kimberly and Evanisko (1981) suggested that a higher level of education leads to higher innovation levels by improving cognitive processing and problem-solving ability. The latter is supported by Glaser (1984), who found that education could produce sophisticated changes in cognitive performance and information processing. In addition, employees with higher levels of education are likely to be more receptive to new ideas and change (Boeker, 1997). Similarly, Kyriakopoulos and de Ruyter (2004) demonstrated that basic knowledge in new circumstances is helpful for solving problems and develop new products and processes, and its usefulness increases if firms have a higher percentage of schooled employees. The empirical study conducted by Smith *et al*. (2005) use the educational level of employees as a measurement a firm's capabilities to introduce new products and services into the market.

The relationship between education and innovation in firms has been analyzed in developing countries by several researchers, specifically in Latin America (Van Uden, Knoben, and Vermeulen, 2016; Goedhuys and Veugelers 2012; Marotta, Mark, Blom, and Thorn, 2007). However, no studies analyzed the effect of employees' educational level on product innovation in Uruguay, although some data provide initial insights on this issue. According to Bianchi and Gras (2003), the number of firms' employees educated in STEM is one key indicator of firms innovative capabilities[4]. In addition, Cassoni and Ramada (2010), focusing on a broad definition of innovation results[5] in Uruguayan manufacturing firms, found that those more likely to innovate have a higher engineer-to-professional ratio among their personnel.

More recently, Aboal, Garda, Lanzilotta, and Perera (2015) have shown that the type of innovation affects the type of employment. Product innovation demands skilled labor when high-tech firms do innovate, but it is important to note that most manufacturing firms in Uruguay are low tech. Thus, because most findings suggest a positive relationship between employees' educational level and the likelihood of product innovation in firms, the first hypothesis of this study is

H1: *The higher the percentage of educated workers within a firm, the higher its probability of producing innovative output.*

However, there are several reasons to think that this relationship is mediated by a firm's structural characteristics, most importantly, its size. As mentioned previously, approximately 60% of small firms in Uruguay did not have any college-educated employees in 2013-2015. This

[4] Innovation capabilities considered in this study are internal or external R&D, capital goods acquisition towards innovation, hardware and software for innovation purposes, technology transfer, industrial design, management and training improvements oriented to processes or product development or to organizational or marketing innovations.
[5] In this study, product, process, organizational, and marketing innovation were considered when measuring innovation results, weighted by their degree of novelty (innovation at the firm level, local, or external market).

negative association between educated workers and the firm size was first found in the 80s (Argenti *et al.*, 1988; Bianchi *et al.*, 2011). No studies have investigated the combination of both variables on product innovation results. Therefore, it is hypothesized that

H1a: *The smaller the firm, the stronger the effect of the percentage of educated employees on product innovation.*

2.2.2 Training and innovation

Training allows employees to acquire new skills, enriching the innovative capability of firms (Shipton, West, Patterson, Birdi, and Dawson, 2006). Internal training helps employees to solve problems efficiently and to understand better firm goals, further stimulating creativity (Giles, van Knippenberg, and Jing, 2017). Several studies have focused on the relationship between training and innovation. Internal training is one of the most critical drivers for product or service innovation in the Danish wholesale trade and ICT-intensive service sectors (Laursen and Foss, 2003). Li, Zhao, and Liu (2006) found that employee training has direct and positive effects on product and technological innovations in Chinese high-tech firms. Dostie (2018) provided compelling evidence about the influence that training has on innovation. He found that both firm-sponsored classrooms and on-the-job training have a positive impact on innovation performance, measured as new products and new processes. By including workplace fixed effects and allowing for time-varying productivity shocks, Dostie (2018) demonstrates that investing more in training leads to more product and process innovation when controlling for other critical dimensions such as turnover and workforce composition. In addition, the Organization for Economic Cooperation and Development (OECD) (2011) found that training contributes to a firm's technological development, and it is positively associated with innovation.

Three pieces of research are of particular interest to this study. First, Nazarov and Akhmedjonov (2012) investigated the determinants of a firm's technological upgrading using product, service, and quality accreditations in the former Soviet republics. They found that internal training increases a firm's ability to innovate, while investment in education does not. The researchers concluded that a firm's ability to innovate in Soviet-transition countries depends on absorbing new technology, not on inventing it; thus, internal training is more important than formal education for innovation because the former helps in adapting new technologies and the latter in its creation. Second, Sung and Choi (2014) found that the objective measurement of training investment increases managers' subjective appreciation of product innovation in South Korean companies. These firms created a climate of constant learning, thereby facilitating the exchange of knowledge among employees, which enhanced these firms' innovation. A positive relationship between internal training and product or process innovation in Norweigan firms was found by Børing (2017). His research highlights that this positive relationship is maintained even when controlled by some human resource management practices in the firm, such as brainstorming sessions and work teams.

Only a few studies have explored the association between training and innovation in Latin America. Fiszbein, Cumsille, and Cueva (2016) shows the heterogeneity and inequality of training among Latin-American firms. Specifically, they found that less-educated employees receive less training than educated employees. González-Velosa, Rosas, and Flores' study (2016) also provides similar evidence that compared to other developing regions, Latin-American firms are well-positioned regarding offering internal training, but skilled workers receive more training than unskilled workers. Also, they discovered differences between more innovative and less innovative firms; the former provide more training to their employees than the latter. Consistent with the theoretical argument that the absence of innovative skill-intensive technologies limits the demand for more training of skilled labor, these studies show that training is not perceived as an important barrier to a firm operation because less-innovative firms do not see training as necessary.

Specifically for Uruguay, Quiñones, Segantini, and Supervielle (2012) found that firms that provide training more often are those that have a more professional human resource management, especially when the firm incorporates new technologies. De Mendoza, Di Capua, and Rucci (2014) found that Uruguayan manufacturing and service establishments that are knowledgeable about the value that human resources can provide to innovative activities are more likely to train their employees. In addition, most quality-certificated companies or those with R&D departments trained their employees more often and introduced innovations. By contrast, almost half of the Uruguayan firms that did not train their staff did not innovate (De Mendoza *et al.*, 2014).

These findings support that there is a relationship between training and innovation in Uruguayan firms, although it has not been analyzed statistically. To address this lack of research, this study hypothesizes states that:

H2: *The higher the percentage of internally trained employees, the higher the probability of producing innovative output.*

As discussed previously, training was more frequently offered in large firms in Uruguay (25% from 2006 to 2015). However, even among large firms, the percentage of manufacturing companies that provides internal training has been declining. Among small firms, those that offered internal training ranged between 5% and 10% over this period. Thus, the relationship between training and size is central to the Uruguayan manufacturing industry. Therefore, this study hypothesizes,

H2a: *The smaller the firm, the higher the impact of the percentage of employees who received internal training on product innovation*

2.2.3 Firms' internal social relationships and innovation

Based on Polanyi (1975), Nonaka and Takeuchi (1995) developed an approach that distinguishes between tacit and codified knowledge. Tacit knowledge is internalized information, which is difficult to formalize and communicate with other workers. Codified knowledge is formalized information that we are aware, and for that reason, it is more straightforward to transfer between colleagues. Thus, an efficient way of knowledge creation can be achieved in firms through the development of a synergistic relationship between tacit and codified knowledge. The design of social processes within firms that transform tacit into explicit knowledge foster knowledge creation and creativity, essential inputs for innovation.

Social capital is a concept that addresses the ideas of Polanyi (1975) and Nonaka and Takeuchi (1995). Structural and relational embeddedness are the two social capital dimensions (Granovetter, 1992). The former relates to the structure of networks determining with whom each person maintains contact; the latter focuses on the quality of these relationships. From the intellectual capital approach, Subramaniam and Youndt (2005) found that social capital moderates the effect that human capital has on innovation directly. However, according to Cabello-Medina *et al*. (2011), social capital contributes to the improvement of innovation performance indirectly through its positive effect on human capital, which affects innovation positively. Beyond its nuances, both studies agree that social capital exerts some positive influence on innovation and also affects its relationship with human capital.

From human resources management (HRM) perspective, Hayton's (2003) investigated discretionary HRM policies and their relationship with firms' innovation. The application of participation mechanisms, empowerment, and specific incentives for employees might allow for the discovery, diffusion, or utilization of local and tacit knowledge in American SMEs. This research suggests that "these activities promote employee discretionary contributions. That is, they encourage the kind of voluntary, helping, and cooperative behavior that supports the development of social capital and thereby encourages knowledge creation and exchange." (Hayton, 2003; p 388). However, focusing only on the HRM costs has little influence on a firm's ability to innovate, accept the risk, and identify and exploit entrepreneurial opportunities.

Using a similar approach, Sung and Choi (2014) found that the importance of knowledge for innovation lies in the connections among people instead of knowledge as an individual asset. In generating product innovations, collective processes based on groups of practice, distributed expertise, and processes that link individuals and collective bodies seem to play a more critical role than knowledge embedded in individual employees. These findings are supported by the previous research of Shipton *et al.* (2006), who found that teamworking and contingent payments are predictors of product innovation.

These ideas of codifying tacit knowledge have been incorporated into the Total Quality Management (TQM) approach. TQM promotes collaborative practices, reduces complexity, and integrates internal and external knowledge (Yusr, Sany Sanuri, Othman, and Sulaiman, 2016; Hsu and Shen, 2005). These practices enhance knowledge management processes that impact positively on innovation results.

In Latin America, the research has focused little on the relational side of human resource practices and innovation. However, some studies provide evidence of HRM characteristics in this region. The commonly accepted fact is that the creation and implementation of HRM practices in Latin America have faced cultural barriers (Elvira and Davila, 2005; Rodriguez and Gomez, 2009). For example, De Forest (1994) indicates that staffing policies in Mexico are based on personal relationships, while in Chile they are grounded in social bonds with an authoritarian top-down approach and male chauvinism (Rodriguez, 2010; Perez Arrau, Eades, and Wilson, 2012). Scholars appear to agree that there is a preference for excessive authority centralization and rigid organizational hierarchies in the implementation of HRM practices in the region (Elvira and Davila, 2005). These characteristics in the Latin-American context are contrary to the features of a pro-innovation HRM style. In this sense, there is evidence that more rigid and centralized organizations may obstruct communication fluxes (Schmidt, 2005).

In Uruguay, Rama and Silveira (1991) studied firms' HRM policies in relation to four economic sectors. In times of economic transformation in which the country became involved in global competition, they found that high levels of physical capital investment were achieved without human capital investment, referred to as "incongruous modernization." The human side of the production is not recognized in Uruguayan manufacturing firms. Quiñones *et al*. (2012) extended the work of Rama and Silveira (1991) finding that while the number of human resource (HR) offices in the manufacturing industry increased between 1991-2010, they are still trying to gain legitimacy within the companies. For example, employees are often evaluated based on personal relationships with owners and top managers rather than on their performance (Quiñones *et al*., 2012). HR offices are still highly dependent on the owners and supervisors, thus complicating human resources' professional management. Similar findings were highlighted by Labadie (2005), who identified that most firms apply HR management with little focus on activities such as compensation, performance evaluation, and training.

One of the few statistical studies investigating HRM in Uruguay was conducted by Bello-Pintado (2015). However, his focus was the relationship between HRM and firm performance in the manufacturing industry, not with innovation. Based on the research conducted by Jiang, Lepak, Han, Hong, Kim, and Winkler (2012) and Jiang, Lepak, Jia, and Baer (2012), Bello-Pintado examined the effect of the abilities, motivation, and opportunities (AMO) framework on firm's performance. He found that in the Uruguayan context, motivation is the key to the effectiveness of an HRM system, and the effects of HRM practices aimed at increasing the skills and involvement of workers have a positive and synergistic effect on performance, but only if practices enhancing the motivation of workers have also been implemented.

Past research emphasizes that internal social relationships are critical for innovation results. In developed economies, there is evidence of a relational based approach to HRM stimulates innovation. However, previous Latin-American and Uruguayan studies have not focused on the relationship between HRM approach and innovation. Therefore, this research hypothesizes,

H3: *The more widespread the application of a relational based approach to human resource management in the firm, the higher the probability of product innovation.*

Evidence from various studies has shown that employee communication, motivation, and proactivity enhance innovation. Hayton (2003) found that employee discretionary behavior encourages a firm's innovation results, especially in high-tech sectors. Cabello-Medina *et al.* (2011) found that social capital affects innovation indirectly by influencing human capital, which has a direct effect on innovation. According to Subramaniam and Youndt's (2005) research, social capital moderates the impact of human capital on innovation. Since it is not possible to measure a firm’s social capital by distinguishing it from the tools to incentivize it using UIS, this research uses them as proxies in two sub-hypothesis for hypothesis 3,

H3a*: The more widespread the application of a relational-based approach to human resource management in a firm, the stronger the influence of educated employees on innovation results.*

H3b: *The more widespread the application of a relational-based approach to human resource management in a firm, the stronger the influence of the share of firms’ trained employees on innovation results.*

3. DATA AND METHODS

3.1. Data

In Latin America, the measurement of firm-level innovation activities is based on recommendations from either the Oslo Manual (OECD, 1992) or the Bogotá Manual (RICYT, 2001). The latter is an adaptation of the Oslo Manual to Latin America, incorporates measurement tools and procedures to capture the characteristics of a firm's technological behavior in this region. Based on the Bogotá Manual, in Uruguay, UIS surveys collect information on a firm's innovation activities, the human and financial resources specified for innovation, their relationships with other agents, the obstacles perceived, and a firm’s innovation results, among other innovation-related issues. ANII develops this survey in Uruguay.

To test the hypotheses proposed in this study, a unique dataset combines six UIS databases available in for period 1998-2015, provided by the Instituto de Economía, Universidad de la República, Uruguay[6]. Every UIS dataset is a triennial measurement, containing companies’ from manufacturing industries and selected services activities for the last two waves (2010-12 and 2013-

[6] I'm thankful to the Instituto de Economia, Universidad de la República, especially to Dr. Carlos Bianchi and B.Sc Felipe Berruti, who kindly provide the UIS panel database for this study.

15). Since the focus of this study is companies of the manufacturing industry, those firms belonging to the service sector for those years were removed.

To be potentially selected, a firm's average triennial employment has to be higher than or equal to ten employees after the 2007-2009 UIS. In previous UIS, firms had to have five employees or more. Large companies[7] were always forcefully included in UIS samples[8]. Medium and small companies were selected through a stratified random sample and within each stratum, they were selected independently under a systematic randomized design, ordering the companies according to their four-digit activity (ISIC, revision 3 until 2007-2009 and revision 4 onward) and the average level of employment in the triennium.

However, the probability of being selected for the UIS is not entirely random for these companies; selection positively correlates with firm size and turnover. For that reason, results must be taken carefully and assessed for the specific biases and limitations. Also, it is important to highlight that the panel dataset was intentionally balanced to take analytical advantage of it. For the research reported here, only the manufacturing firms that were included from the third UIS (2004-2006) to the last one (2013-2015), due to different variable measurements in the 1998-2000 and 2001-2003 waves[9]. This strategy reduces the number of cases in the dataset, especially small firms. For that reason, these results must be taken with caution, considering the final structure of the panel dataset, which is available in Table 1.

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[7] Large firms, those with 100 employees or more, and companies with a turnover larger than an amount that varies between 1 and 4 million US dollars are forcedly included.

[8] Large firms for the Uruguayan case, those more than 50 employees or with an annual turnover to a specific amount that varied across the period from 1 million to 4 million dollars were also forcefully included. Also, until 2009 companies, which had average employed personnel in the triennium of 5 employees or more were in the random sample.

[9] In appendix B it is explained the variables used and the reasons for excluding 1998-2000 and 2001-2003 waves.

Table 1 – Panel data structure, by product innovation achievement; OECD tech intensity levels and size, 2004-2006, 2013-2015

		Product innovation							
		2004-2006		**2007-2009**		**2010-2012**		**2013-2015**	
Technology intensity (OCDE)	Total firms (%)	Yes	No	Yes	No	Yes	No	Yes	No
		32.2	67.8	31.4	68.6	27	73	30.6	69.4
Low-tech industries	62%	17.4	44.4	17.9	43.9	13.5	48.3	17.7	44.2
Medium-low tech industries	15%	3.6	10.6	3.9	11.4	4.4	10.9	3.6	11.4
Medium-high tech industries	14%	6	8.8	5.2	8.6	4.9	8.8	5.5	8.6
High-tech industries	9%	5.2	3.9	4.4	4.7	4.2	4.9	3.9	5.2
		2004-2006		**2007-2009**		**2010-2012**		**2013-2015**	
FIRM SIZE		Yes	No	Yes	No	Yes	No	Yes	No
		32.2	67.8	31.4	68.6	27	73	30.6	69.4
Small		1	4.9	0	6.2	0	0.3	0.3	0.3
Medium		15.8	41.6	14	36.9	2.1	15.1	15.1	14.3
Large		15.3	21.3	17.4	25.5	24.9	57.7	57.7	54.8

Source: UIS database, own elaboration. Note: OCDE manufacturing industries classification based on R&D intensities can be accessed in OECD (2011). Note: Small firms represent those with 5-19 employees, medium-size 20-99 employees, and large-firms more than 99 employees. Since the number of firms by size measured using occupation varies per panel wave, this data is not shown for the whole dataset, contrarily to the technological intensity, which does not vary for each wave.

Thus, small firms (those fewer than 20 employees) are virtually inexistent in the final data structure. In addition, the dataset is skewed toward low-tech manufacturing industries. Approximately one-third of the companies are low-tech firms (62%). Among firms that introduced a product innovation, the vast majority belong to this technological level. The other two-thirds of this dataset are composed of medium-low tech industries (15%), medium-high tech industries (14%), and high-tech industries (9%). Even though these biases of the panel dataset, its use has significant advantages. It allows controlling for time-invariant unobservable firm characteristics, providing a broad set of time-varying observable characteristics.

3.2. Dependent variable

At the firm level, innovation can be studied in two ways – first, through an *ex-ante* examination of the firm´s innovation capabilities, and second, through an *ex-post* analysis of their practical innovation results. Given that most of the previous research on the relationship between innovation and human capital has focused on innovation results, the dependent variable of this research will measure such outcomes. More specifically, most studies investigated the effect of human capital on product innovation. Thus, in this study, product innovation is the dependent variable, allowing this research to be comparable to other investigations of this issue. Specifically, the dependent variable (PRODIN) is a dichotomous one, which measures whether the firm has made a product innovation (1=Yes) in the last three years or not (0 = No).

Studies that have explored the relationship between human capital and innovation results have employed different approaches regarding measuring the latter. According to the Bogotá Manual definitions, an innovation outcome can be a new product, a new production process, a new organizational method, or a new method of commercialization. Previous research focuses primarily on product innovation, secondly process innovation, rarely evaluating evaluates organizational or marketing innovation. Information about the dependent variables in previous studies, differentiating whether they measured innovation activities or results is provided in Appendix A. Also, the data in Appendix A provide information on if the dependent variables measured product, process, organizational, or commercialization innovation.

The level of innovation matters. For this reason, a second dependent variable was tested aimed to measure whether product innovation reached the local or the international market (PRODIN-MKT). Due to the small number of cases innovated in the global markets, local and international innovation was merged into one dummy variable. In this case, the variable is coded "1" if the product reaches either the local or international market. Otherwise, the variable is coded "0." The objective of creating this dummy variable was to compare those firms that innovated at the firm level and those that took more risky innovations, reaching the local and international markets[10].

3.3. Independent variables

Educated employees is the first independent variable, defined as workers with at least a college or a technical degree. The percentage of educated employees was used to test hypothesis 1. This variable was measured by asking the firm how many of their employees working in a typical month last year had at least a college or a technical degree. The percentage of employees with at least a college or technical degree in the firm was considered as a proxy for the amount of codified knowledge in it. This variable has been used in several studies that investigated the relationship between human capital and innovation as a representation for a firm's knowledge base (De Winne and Sels, 2010; Smith *et al.*, 2013; van Uden *et al*., 2016).

Similar to Dostie (2018), the percentage of employees who received internal training (TRAIN) was used to test Hypothesis 2. All firms that declare having conducted some internal training had to report employees who received it. Then this number was divided by firms' total number of employees. The third independent variable is the Relational-based HRM tools (HRM), used to test Hypothesis 3. This variable is an index that measures the breadth of the application of relational-based HRM tools on firms. Similar to De Winne and Sels (2010), this index was developed using the equally weighted sum of the following five binary variables:

- Firm hierarchy reduction (1=Yes, 0=No): More rigid and centralized organizations may obstruct communication flows (Schmidt, 2005). Thus, this variable measures for the reduction of organizational levels during three years.

[10] Uruguayan manufacturing industry mostly exports to regional markets, not to the most industrialized ones. That can make less sophisticated the innovation that reaches external markets compared to those that enter the local market. Thus, combining both variables would not imply very different technological levels.

- Application of systematic mechanisms to obtain employees' opinions (1=Yes, 0=No): this variable measures employees' influence on decision making, associated positively to firm's product innovation (Hayton, 2003; Sung and Choi, 2014)
- Creation of collaboration teams in the firm (1=Yes, 0=No); this variable accounted for teamwork, which influences a firm's product innovation (Shipton *et al*., 2006)
- Creation of continuous improvement teams (1=Yes, 0=No); Total Quality Management (TQM) practices and innovation are positively related (Hsu and Shen, 2005; Yusr *et al*., 2016) and imply the use of codification tools for tacit knowledge.
- Application of results-based economic stimuli (1=Yes, 0=No). Motivation enhances innovation (Sung and Choi, 2014; Shipton *et al*., 2006; Hayton, 2003) and there is also evidence that in the Uruguayan context, a set of motivation tools fosters the effectiveness of a set of HRM tools (Bello-Pintado, 2015). Assigning results-based economic incentives may foster employees' motivation.

Each variable was equally weighted and then combined, creating a new variable ranging from 0-1. When this variable indicated 0, there were no relational-based HRM tools applied in the firm, while if this variable indicated 1, the maximum level of tools were applied.

3.4. Control variables

A set of variables was also added to the analysis to control for a firm's observable characteristics. The size of the company (SIZE), measured by the number of employees in logs, was included. The most common rationale for the log transformation is to reduce variance distribution of the values across observations. The implicit reasoning for the log transformation relies on the fact that data on the number of employees are sometimes highly skewed, and extreme scores can cause biases (Kimberly and Evanisko, 1981). Previous research supports that, notwithstanding nuances regarding methodologies used, the size of the firm influences innovation activities and results in Uruguay (Cassoni and Ramada, 2010; Pittaluga *et al.*, 2005; Bianchi, 2007).

The presence or absence of foreign capital (FK) in the firm is a dummy variable coded 1=Yes or 0=No. This variable was included because firms in developing countries often benefit from the technological knowledge available from their headquarters (Isobe, Makino, and Montgomery, 2000). However, for the Uruguayan case, Bianchi (2007) did not find a strong correlation between the development of innovation capacities and the presence of foreign capital in the firm. Pittaluga *et al.* (2005) found a similar result from the first UIS, conducted from 1998 to 2000. Cassoni and Ramada-Sarasola (2015) found that multinationals and exporters generated innovations of enhanced value compared to those of local market-oriented firms. Based on these previous studies, it was not possible to forecast the relationship between innovation results and the presence of foreign capital, but it was a key dimension to include as a control.

In addition, the propensity of export (EXP) has been found to show a weak positive association between higher export performance and a firm's innovative capacity (Bianchi, 2007). However, recent research on Uruguayan industry demonstrated a weak positive relationship or bi-directional effect (Resnichenko, 2017; Peluffo and Silva, 2016). In this study, the percentage of exports in total sales standardized by 2005 prices is used. Based on previous results using panel datasets, a positive relationship between EXP and product innovation is expected (Bianchi *et al.*, 2015).

The firm's internal capacity to create knowledge influences innovation outcomes (Cohen and Levinthal, 1990). As such, a variable that indicates a firm's internal R&D investment relative to the number of employees was included (adjusted by 2005 prices). Also, this variable was intended as a proxy for firms' innovation strategy. A firm that pursued a strategy based on internal R&D investment (in-house innovation) were more likely to innovate in new products (Zuniga and Crespi, 2013). Zuniga and Crespi's (2013), found that these strategies had different impacts on the labor skills needed. For that reason, a similar variable aimed to measure the amount invested in purchasing external technology for innovation was included. This variable indicated the firms' investment per employee in capital goods, ICT, external R&D, and external consultancies (adjusted by 2005 prices). These variables were labeled "make" and "buy" innovation, respectively (MAKESTRAT, BUYSTRAT). These variables were squared to account for decreasing marginal returns ($MAKESTRAT^2$, $BUYSTRAT^2$). A proxy for external linkages was also included as a dummy variable coded 1 if the company made cooperation agreements or participated in an enterprise network over the period investigated, and 0 if not (COPNET). Based on national and international studies (Jensen, Johnson, Lorenz, and Lundvall, 2007; Bianchi *et al.*, 2011; Bianchi and Gras, 2003; Cohen and Levinthal, 1990), a positive correlation is expected between cooperative activities and innovation.

3.5 Analyses

Since both dependent variables (PRODIN or PRODIN-MKT) had a discrete distribution, logistic regressions are applied. The improvement of overall model fit was used to identify the appropriate models for hypothesis testing, based on log-likelihood tests (Osborne, 2017; Long, 2012). For formal hypothesis tests, conditional effect-specific relevant values of the independent variables are reported. In addition, we provide graphs that show predicted probabilities for significant interaction effects across the range of observed variable values. Equation 1 is the baseline model (Model 1) that aims to identify the effect of the variables on product innovation (at the firm or market levels);

$$ln\left(\frac{P\ prodin}{1 - P\ prodin}\right)_{i,t} = \alpha + \beta_1 prof_{i,t} + \beta_2 train_{i,t} + \beta_3 hrm_{i,t} + \varphi_{i,t} x + \delta_i + \gamma_t + \varepsilon_{it} \qquad \text{[Eq 1]}$$

where $ln\left(\frac{p\ prodin}{1 - p\ prodin}\right)_{i,t}$ is the natural logarithm of the conditional odds for a firm *i* to achieve a product innovation in year *t* [11]. The coefficient β_1 quantifies educated workers share effect for firm *i* at year *t*; β_2 is the coefficient that estimates the effect a firm proportion of employees who received training on the odds of producing an innovation for firm *i* at year *t*; while β_3 is the coefficient that indicates HRM effect for firm *i* at year *t*. The vector $\varphi_{i,t}$ contains the defined control variables for firm *i* at year *t*. The first step to disentangling sources of potential bias is adding a firm's fixed-effects. Firm-level characteristics (δ) that are correlated with both human capital and innovation performance can introduce biases in our coefficients. For example, if high-ability managers introduce more innovations and invest more in human capital, its real impact on innovation could be biased. Thus, δ_i and γ_t are a firm's and year fixed-effects respectively, and the error term is defined by ε_{it} for firm *i* at year *t*.

To test Hypothesis 1b and 2b requires integrating the firm's size moderation. To test both effects, we define Model 2 as

$$ln\left(\frac{p_{prodin}}{1 - p_{prodin}}\right)_{i,t} = \alpha + prof_{i,t} + \beta_2 train_{i,t} + \beta_3 hrm_{i,t} + \theta\ (prof_{i,t} * size_{i,t}) + \zeta(train_{i,t} * size_{i,t}) + \varphi_{i,t} x + \delta_i + \gamma_t + \varepsilon_{it} \qquad \text{[Eq2]}$$

Equation 2 incorporates two new parameters. The first (θ) accounts for the interaction term between educated workers and size, and the second (ζ) captures the multiplicative effect between training and size. To further evaluate Hypothesis 1b and 2b, Model 3 is used.

[11] When modeling product innovation (for the local or external market), the variable modeled also has a discrete distribution. Logistic regression is applied with firm fixed effects is also applied. Equation 1 changes for these set of models: The dependent variable $ln\left(\frac{p\_innov\_ext}{1 - p\_innov\_ext}\right)_{i,t}$ is defined as the natural logarithm of the conditional odds for a firm *i* to achieve external to the firm innovation in year *t*.

$$ln\left(\frac{p_{prodin}}{1-p_{prodin}}\right)_{i,t} = \alpha + \beta_1 prof_{i,t} + \beta_2 train_{i,t} + \beta_3 hrm_{i,t} + \tau\,(prof_{i,t} * hrm_{i,t}) + \psi\,(train_{i,t} * hrm_{i,t}) + \varphi_{i,t}x + \delta_i + \gamma_t + \varepsilon_{it} \quad \text{[Eq3]}$$

Equation 3 defines this model, adding two interaction terms to Equation 1. One parameter *(τ)* captures the multiplicative effect between educated workers and HRM, while the second (ψ) does the same but between HRM and training. In Table 2, we summarize the hypotheses of this study:

Table 2 – Summary of Hypothesis and Expected Relationships

		Equation	Coefficient	Expected sign
Educated workers	Hypothesis 1	1	β_1	+
Training	Hypothesis 2	1	β_2	+
HRM	Hypothesis 3	1	β_3	+
Educated workers * Size	Hypothesis 1a	2	θ	-
Training * Size	Hypothesis 2a	2	ζ	-
Educated workers * HRM index	Hypothesis 3a	3	τ	+
Training * HRM index	Hypothesis 3b	3	ψ	+

These models have their limitations. There are concerns of potential sources of bias that might lead to simultaneity between human capital and innovation. First, firm-level innovation in itself can lead to or require firm-sponsored training and more professionals. For example, a new product can be a consequence of a new production process. Employees would need training on this process, and, an experienced engineer may be hired to train them. This complicated relationship is by no means easy to disentangle. Even when considering lagging dependent variables, previous trends in product innovation that can affect them must be taken into account. For that reason, a new design is needed to understand the actual causality between human capital and innovation. Thus, this research aims to identify associations using panel data controlling for firms' unobserved characteristics.

4. RESULTS

4.1. Internal product innovation

The outcomes of the binary logistic regressions specified for product innovation are listed in Table 1. All variables were standardized using Z-scores. All models were calculated using robust errors, allowing for the clustering of errors by firm. In addition, random and fixed effects models were included to test for the consistency of both estimators, with inconsistency being found for the random effects models in all cases, as can be seen in Appendix D. Model 1 regresses product innovation; Model 2 examines the interactions between SIZE with TRAIN and REMP, and Model 3 examines how HRM index interacts with EEMP and TRAIN.

Model 1 exhibited an initial -2 log-likelihood of -248.9 (χ^2 = 44.16, p-value < 0.0001). All control variables indicated the expected signs, and, all coefficients were significant or nearly significant except for FK and EXP. The variables MAKESRAT2 and COPNET were almost significant at a 90% confidence level while SIZE and BUYSTRAT2 exhibited significant effects on firm product innovation at a 5% and 1% level, respectively. The key explanatory variables, EEMP did not exhibit a significant effect on the likelihood of a firm's product innovation. TRAIN and HRM exhibited a significant influence on firms' probability of product innovation at a 1% and 5% correspondingly, showing the positive sign expected in hypotheses 2 and 3.

Table 3 – Logistic Regression Estimations, Firm Product Innovation

	Model 1 (PRODIN = 1)	Model 2 (PRODIN = 1)	Model 3 (PRODIN = 1)
TRAIN	0.332**	0.346**	0.465***
	(0.111)	(0.119)	(0.139)
EEMP	0.0943	-0.0318	0.0875
	(0.122)	(0.157)	(0.117)
HRM	0.277*	0.317**	0.277*
	(0.110)	(0.113)	(0.109)
TRAIN * SIZE		0.273*	
		(0.128)	
EEMP * SIZE		-0.316*	
		(0.161)	
TRAIN * HRM			-0.135
			(0.0905)
EEMP * HRM			-0.0553
			(0.102)
SIZE	1.152*	1.080*	1.128*
	(0.547)	(0.544)	(0.548)
EXP	0.104	0.129	0.0803
	(0.212)	(0.206)	(0.206)
MAKESTRAT	1.537+	1.528+	1.542+
	(0.842)	(0.863)	(0.846)
MAKESTRAT2	-0.0911+	-0.0933+	-0.0910+
	(0.0508)	(0.0531)	(0.0509)
BUYSTRAT	0.783**	0.828**	0.761**
	(0.253)	(0.262)	(0.246)
BUYSTRAT2	-0.0527**	-0.0574**	-0.0511**
	(0.0179)	(0.0187)	(0.0176)
FK	-0.147	-0.100	-0.138
	(0.405)	(0.419)	(0.400)
COPNET	0.443+	0.475*	0.434+
	(0.233)	(0.234)	(0.233)
Firm-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
N	*792*	*792*	*792*
-2 log-likelihood	*-248.9*	*-244.5*	*-247.9*
Wald χ^2	*44.16, p-value < 0.0001*	*44.52, p-value < 0.0002*	*45.84, p-value < 0.0001*

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 2 includes the two-way interactions between SIZE and both TRAIN and EEMP to test Hypotheses 1a and 2a. The inclusion of these interaction terms significantly improved the model fit (log-likelihood, 244.5, $\chi^2 = 44.52$, p-value < 0.0002). As Table 3 shows, in Model 2 HRM increased its significance to a 1% level. Both interactions were significant at the 5% level, but only EEMP*SIZE is negative as expected. The inclusion of the interaction effects in Model 2 increased

COPNET significance to 5% level. FK and EXP remained insignificant, MAKESTRAT2 was almost significance at a 10% level, and BUYSTRAT2, as well as COPNET, showed the expected sign and significance at a 5% level.

Model 3 evaluates the interactions between HRM and EEMP, and HRM and TRAIN. The model had a significant effect in explaining product innovation variance and a higher -2 log-likelihood (-47.9) than Model 2. However, the interaction terms were not statistically significant, although the multiplicative effect of HRM and TRAIN was almost significant at the 90% level. Consequently, Hypotheses 1b and 2b are not confirmed: HRM did not have a multiplicative effect on both EEMP and TRAIN. Because the inclusion of the interaction between the HRM and both TRAIN and EEMP also change COPNET to almost significant as in Model 1. The remaining control variables did not change their significant levels nor signs.

4.2. Market product innovation

The outcomes of the binary logistic regressions using market product innovation as the dependent variable are listed in Table 4. Z-scores were again used to standardize the variables. Similar to Models 1, 2, and 3, robust errors were used, allowing for firm clustering. Random and fixed effects models were tested for the consistency of both estimators, resulting in better consistency for the fixed-effects models, as can be seen in Appendix D. Model 4 is the baseline model that regresses PRODIN-MKT on innovation; Model 5 examines the associations of the interactions between human capital, and size and Model 6 studies how HRM interacts with educated employees and training.

Table 4 – Logistic regression estimations, market product innovation

	Model 4 (PRODIN-MKT = 1)	Model 5 (PRODIN-MKT = 1)	Model 6 (PRODIN-MKT = 1)
TRAIN	0.150	0.186	0.283*
	(0.101)	(0.108)	(0.128)
EEMP	0.0633	0.0383	0.000410
	(0.145)	(0.144)	(0.157)
HRM	0.232*	0.268*	0.245*
	(0.103)	(0.107)	(0.105)
TRAIN * SIZE		0.276**	
		(0.104)	
EEMP * SIZE		-0.139	
		(0.132)	
TRAIN * HRM			-0.147^{+}
			(0.0824)
EEMP * HRM			0.116
			(0.109)
SIZE	1.023*	0.919^{+}	0.979*
	(0.458)	(0.476)	(0.464)
EXP	0.0211	0.0476	0.0341
	(0.241)	(0.235)	(0.233)
MAKESTRAT	0.437*	0.430*	0.434*
	(0.175)	(0.170)	(0.175)
MAKESTRAT2	-0.0222*	-0.0234*	-0.0220*
	(0.0102)	(0.0100)	(0.0103)
BUYSTRAT	0.235	0.227	0.216
	(0.236)	(0.230)	(0.226)
BUYSTRAT2	-0.0136	-0.0132	-0.0120
	(0.0179)	(0.0175)	(0.0178)
FK	-0.430	-0.401	-0.404
	(0.362)	(0.368)	(0.360)
COPNET	0.216	0.190	0.249
	(0.216)	(0.215)	(0.224)
Firm-fixed effects	YES	YES	YES
Time-fixed effects	YES	YES	YES
N	*688*	*688*	*688*
-2 log-likelihood	*-257.905*	*-237.3*	*-238.9*
Wald χ^2	*29.98, p<0.01*	*32.43, p < 0.01*	*32.48*

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 4 was significant in explaining PRODIN-MKT (log-likelihood = -257.9, χ^2 = 29.98, p-value < 0.01). From key independent variables, only HRM influence a firm's external product innovation at a 5% level while EEMP and TRAIN were not significant. The signs of all control variables were as expected. The variable MAKESTRAT2 showed the expected negative direction and a significant effect at a 5% confidence level. SIZE was significant and positive, while BUYSTRAT, BUYSTRAT2, COPNET, FK, and EXP were not significant.

In Model 5, the multiplicative effects between SIZE and both TRAIN and EEMP were introduced to test Hypothesis 1a and 2a for PRODIN-MKT. The inclusion of the two-way interactions did not improve the model fit, but their effects were significant (-log likelihood -237.3, $\chi^2 = 32.43$, $p < 0.01$). The variable SIZE was a moderator only of training, but contrary to Hypothesis 2a its sign was positive. The control variables did not vary in its sign nor significance compared as in Model 4.

The goal of Model 6 is to test Hypotheses 3a and 3b using PRODIN-MKT as the dependent variable. This model was significant, but the inclusion of the two-way interactions between HRM and both TRAIN and EEMP did not improve the model fit (-log likelihood = - 237.9, $\chi 2 = 32.43$, $p < .01$). The interaction terms were not significant, but it is worth mentioning that TRAIN * HRM reached a 90% confidence level and the expected negative sign. The significance and sign of the control variables did not vary compared to Model 4 and 5.

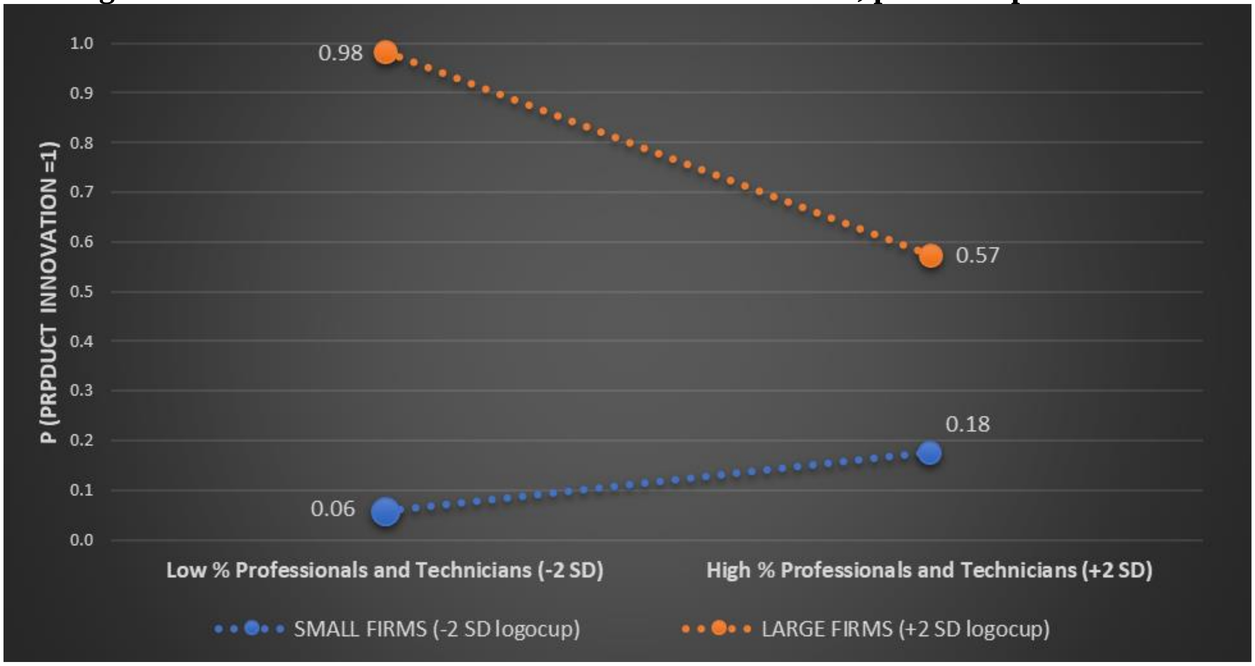
5. DISCUSSION

The findings from this research support previous studies which suggested that, especially in developing countries, innovation occurs primarily at the firm level. Internal firm practices for managing human capital, such as training or fostering human interactions and communication, improve the likelihood of innovation (Hayton, 2003, De Winne and Sels, 2010; Nazarov and Akhmedjonov, 2012; Sung and Choi, 2014; González-Velosa *et al.*, 2016). Updating and sharing employee knowledge seem to be a predictor of a firm's product innovation.

We did not, however, find that the proportion of educated workers is associated with product innovation directly, neither at the firm nor the market level. This result suggests that firm-level practices such as training or human resource management are more beneficial than individual human capital endowments in Uruguayan firms for either firm or market product innovation. However, this situation changes when the firm size is taken into account. As a result, the effect of both the share of educated employees and firm size must be examined together as is shown in Figure 5.

Educated employees enhance product innovation at the firm level for smaller companies as is seen through the interaction effect between SIZE and EEMP in Model 2. To examine these interactions, Figure 5 shows the regression line equation assigning a value of −2 standard deviations in SIZE for small firms and +2 standard deviations in SIZE for large firms. All values were converted from logits to conditional probabilities.

Figure 5 – Interaction between size and educated workers, predicted probabilities



An increase in the share of educated employees (EEMP) tends to increase the conditional probability of product innovation for small firms. However, this term does not increase as much;

the predicted probability increases from 0.06 to 0.18 for those small firms with a +2 SD in EEMP[12]. The apparent weak effect on small firms has to be taken with caution due to the skewness toward large firms in the panel dataset (only 60 cases around -2 SD in SIZE).

Unlike for small firms, there is a reduction in the product innovation probability for large firms when they increase their educated worker's share. As in most developing countries, in Uruguay innovation strategies primarily involve technology acquisition (Bittencourt, 2012). Acquiring the ability necessary to work with machinery and equipment is key for firm-level innovation. As mentioned previously, small companies tend to innovate primarily at the firm level. In addition, the significant values of the buy strategy in Models 1-3 indicate that to innovate at the firm level, adapting external assets to innovate is essential and can create the need for more professionals. However, hiring more professionals than needed can reduce the likelihood of innovation. Because this situation is more likely to occur in larger firms with fewer budget restrictions for hiring educated employees than in small firms, it can explain the negative interaction effect between size and skilled workers seen by the red line in Figure 5.

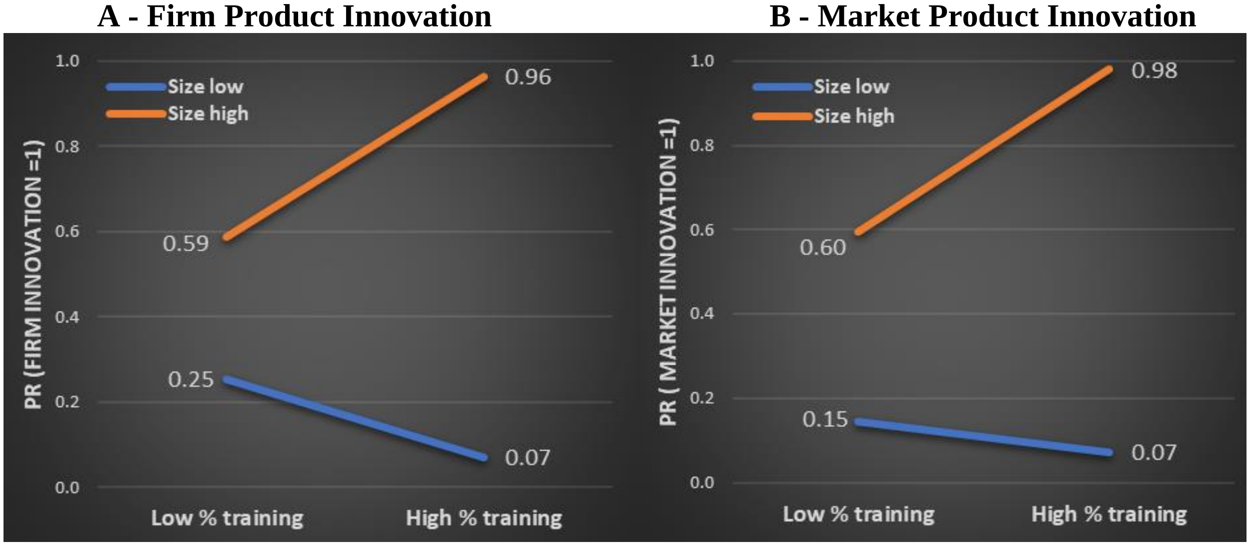
This analysis implies that it is not possible to examine human capital dimensions in a vacuum, a realization that is especially crucial for policymaking. As mentioned earlier, in Uruguay, the number of firms with no educated workers grew during the period of study. More importantly, the number of small and mid-sized manufacturing firms with no professionals increased throughout the study period, as shown in Figure 3. Thus, public policy to foster product innovation by hiring educated workers in Uruguayan manufacturing firms has to target small firms. If small firms increase their number of skilled workers, it is possible to increase to some extent the innovative capacity of the Uruguayan manufacturing industry.

[12] This accounts for approximately 25% of educated workers in its workforce

Figures 6a and 6b show that when size is considered as a moderator, the effect of training on both firm and market innovation change. Contrary to Hypothesis 2a, the sign of the moderator effect between size and training is positive. The predicted probabilities for the interaction effect between size and training are plotted in Figure 6a and 6b. The former shows that a small share of internal trained employees in large firms accounts for a 0.59 predicted probability in a firm's product innovation, increasing to 0.96 for companies with a high share of internally trained employees. For small firms, those that account for a low share of internally trained employees exhibit an innovation probability of 0.25, higher than those companies with a high share (0.07). Market product innovation essentially does not vary when comparing companies with low and high shares of internally trained employees, ranging from only 0.15 to 0.07; however, it is again worth recalling the few small firms in the dataset.

Figure 6 – Interaction between size and training, predicted probabilities

A - Firm Product Innovation **B - Market Product Innovation**



In conclusion, human capital is associated with product innovation. However, not all types of human capital operate in the same way for all companies. For small firms, increasing the number of educated employees fosters the likelihood for product innovation, but it is not the case for large firms with fewer budgetary restrictions for hiring professionals. Even do having more professionals can result in a negative impact on innovating in products. However, for large firms, internal training is a critical factor for increasing their likelihood of product innovation, while it does not seem to be a crucial factor in small companies.

There are also some findings that highlight that the context is a chief dimension when analyzing human capital and innovation. Consistent with Crespi and Rovira (2012), the make strategy contributes significantly to introducing market innovations as is see in Models, 4, 5, and 6. However, the buy strategy is not of influence when evaluating market product innovation. The number of professionals is not associated significantly with market product innovation. Thus, make and buy strategies are related to different sources of human capital for introducing an innovation successfully. Firm-level practices and communication flows seem to be crucial for both levels of innovation (product and market), a result that has been identified for developing countries in previous studies (van Uden *et al*., 2016). Individual human capital aligned with the adaptation of equipment and external knowledge impacts firm-level innovation, but not the local or foreign market innovation.

6. IMPLICATIONS

Other studies found that Uruguay compares well with other regional economies regarding their level of human capital (Iván *et al.*, 2016). However, section 2 of this article has shown how the Uruguayan manufacturing industry has reduced the number of educated employees hired and investment in internal training during the period of study. At the same time, several research pieces and reports have pointed to human capital as one of the leading factors in helping companies increase their innovative behavior. However, this research found that the characteristics of a company, especially its size, and the risk level of innovation are central factors for policy design. It is not just a mattter of increasing the average human capital level, either by hiring more educated employees or investiging more in internal training. These results illustrate that the relationships between innovation and human capital investments is more nuanced that intially hypothesized.

For less risky innovations, those targeted to the firm itself, the policies that might help small firms hiring its first college graduate employee can have a significant impact on the likelihood of this type of innovation. However, the role of internal training and communication flows are useful for innovation at the firm and market level, especially in large firms.

Thus, this paper leads to several policy recommendations. As can be seen in Appendix C, the vast majority of policies aimed to foster innovation in Uruguay through human capital are focused on individual endowments, i.e., hiring more professionals, providing post-graduate studies for firm's employees. The firm's internal level practices, such as training or human resource management, are essentially not mentioned in these policies. Based on the ten policies found and reviewed to the date, only one focuses on internal training, and only one focuses on human resource management practices. Nine of these policies aim to increase the number of skilled workers through either helping companies to hire more professionals or by funding their employees to attend graduate studies.

However, as this study revealed, hiring more professionals can foster product innovation only in small firms. This paper showed that even after controlling for firm's characteristics and economic trends over time, internal firm practices such as training and fostering employee participation, communication, and motivation are positively associated with innovation. The Uruguayan policies aimed to foster innovation through human capital do not focus these factors. There is much innovation capacity to be gained by reshaping Uruguayan innovation policy tools by emphasizing on internal firm's practices toward human capital.

According to Arocena and Sutz (2010), in Uruguay, local characteristics were not sufficiently taken into account in relation to the definition of innovation policies. Internal firm practices such as training, employee decision making, and communication were not adequately considered. Given the relationship between innovation and the human capital dimensions analyzed in this study, innovation policies should, at the very least, redesign objectives to achieve higher levels of product innovation in Uruguay.

7. LIMITATIONS

Does human capital influence innovation or innovation foster human capital? The impossibility of being able to answer this question is the main drawback of this paper. To analyze causation is necessary to design specific research focusing on that objective. It is important also to stress that due to the cross-sectional nature of the UIS, the resulting panel ceases to be representative, skewing the dataset towards high-size firms. However, by using this panel data structure, this study was able to control for firms' time-invariant unobservable characteristics while providing a rich set of time-varying observable characteristics. Another significant limitation is how educated employees were measured. With the available data, only measurements of individual human capital endowments using employees with a college degree can be used. Distinguishing the effects of high-school, technical, or graduate education on innovation is worth investigating. Probably, workers with more specialized education can influence innovation more than workers with only a college degree, but we cannot differentiate between the two with the UIS dataset. Another limitation of this study is that it did not account for firms' survival biases. It was not possible to include those firms that did not survive over the research period since we are working with balanced panel data to maintain the fixed effects. In addition, it is well known that data on firm innovation tend to overestimate successful firms since innovation reduces the firm's death likelihood. Thus, these results are biased toward successful firms. Another limitation is the underestimation of other intangible assets as social capital. As previously mentioned, many studies have found that social capital enhances innovation and, in this relationship, interacts with human capital. In this study, there were no available data for measuring firms' social capital level. Instead, it was possible to measure the firm's intention to create internal social capital through the HRM index.

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CHAPTER THREE

A MATTHEW EFFECT IN ENTREPRENEURIAL FUNDING? AN ANALYSIS OF REPEATED EVENTS

1. INTRODUCTION

Attributes not related to entrepreneurial talent can determine who receives external funding. Previous research found that more than half of emerging ventures' funding comes from the personal contributions of founders (Gartner, Frid, and Alexander, 2012). In addition, more educated and affluent entrepreneurs are significantly more likely to obtain external funding (Gartner, Frid, and Alexander, 2012). Personal wealth is also a primary driver of acquiring external financing (Frid, Wyman, Gartner, and Hechavarria, 2016), reinforced by the circumstance that low-wealth entrepreneurs are less likely to obtain funding from formal institutions (Frid *et al.*, 2016). However, it has also been found that when low and moderately wealthy entrepreneurs get over the gestational phase (Reynolds and Curtin, 2008), their likelihood of abandoning their intentions of becoming a business owner is similar to any other entrepreneur (Frid, Wyman, and Coffey, 2016). Without economic constraints, less privileged entrepreneurs can perform as well as the wealthiest.

Based on the Matthew effect theory (Merton, 1968), which depicts the social phenomenon of accumulated advantage, this study examines the biases in entrepreneurial financing and their effects. Precisely, by using event history analysis, this research estimates the effect of receiving recurrent funding for firm creation and survival. Also, this research sheds light on the factors associated with receiving recurrent financing during the early entrepreneurial stages, applying event history analysis for repetitive events.

The estimates of this research result in several contributions. First, the study shows that the recurrence and timing of the external funding received by entrepreneurs matters for firm survival and creation. Second, this project found that some characteristics pointed out by the Matthew effect theory shapes the entrepreneurial reward system, such as the entrepreneur's socio-economic background, but also some specific actions that entrepreneurs can take toward reducing asymmetrical information between them and lending agents. Finally, from a methodological perspective, this research highlights the necessity to account for the repeated nature of the funding event when analyzing entrepreneurial financing.

2. THEORY DEVELOPMENT AND HYPOTHESES

2.1 The Mathew Effect

External funding increases the likelihood for an entrepreneur to create a new company and reduces the probability of not being successful in this endeavor (Hechavarría, Matthews, and Reynolds, 2016). However, previous research has found that the possibility of being funded is not directly related to entrepreneurship talent. Several personal characteristics such as wealth, ethnicity, and other intangibles like human and social capital increase their probability of receiving these funds (Frid, Wyman, and Coffey, 2016; Frid, Wyman, Gartner, and Hechavarria, 2016; Frid, 2014; Gartner, Frid, and Alexander, 2012). Merton (1968) developed a framework for explaining why higher economic and social status actors receive greater rewards, such as funding, than those at a lower status for a similar activity. He turns this situation the Matthew effect[13] when rewards

[13] Inspired in the Bible verse found in the Gospel of Matthew: "For whosoever hath, to him shall be given, and he shall have more abundance: but whosoever hath not, from him shall be taken away even that he hath."

are allocated based on social status and not on the efforts made. As a result, a self-reinforcing mechanism appears in a reward system.

Fields such as Science and Technology and Society examined how access to funding reinforces a trajectory of gaining new grants, does confirming the Mathew effect (Azoulay, Stuart, and Wang, 2014; Petersen *et al*., 2013; Arora, David, and Gambardella, 1998; Arora and Gambardella, 1997; David, 1994; Medoff, 2006; Zuckerman, 1972). The self-reinforcement trajectory increases research group productivity and explains the increasing concentration of publications around a stable group of scholars. Further, successful grant funding impacts positively on a research group due to a cumulative advantage based on the positive feedback between research and resources, in turn, increasing a team's productivity (David, 1994). However, a reputation effect can also explain this increase in productivity, which emerges when other researchers focus their attention on the work of “the elite” (Arora *et al*., 1998; Medoff, 2006), minimizing allocation time in the search for new relevant publications. David (1994) claims that the “Matthew effect” could lead to a stable equilibrium, where the allocation of funds is targeted not necessarily on projects’ quality, but rather on the number of citations that a particular researcher has. In Economics (Pereira and Suárez, 2017; Antonelli and Crespi, 2013; Medoff, 2006) and Education (Glasswell, 2001; Stanovich, 1986) the Mathew effect has been tested as well, the results finding a similar pattern.

Two theoretical considerations make the Matthew Effect worth investigating in Entrepreneurship Studies, first, the asymmetrical information between lenders and entrepreneurs, and second, the high transaction costs of the small business loan market. Asymmetrical information (Rothschild and Stiglitz, 1976; Akerlof, 1970) is found when there is unbalanced information between supply and demand, leading to inefficient outcomes in specific markets.

Since new ventures typically do not disclose financial information about their trade, products, and services, asymmetric information is particularly problematic for small business loans (Berger and Udell, 1998). Lenders have to monitor borrowers, leading to a second theoretical argument for investigating the Matthew effect in entrepreneurship: the high transaction costs (Coase, 1937) of the entrepreneurial loan market. While these costs are not problematic for larger companies, they can make these loans unreachable for NEs. Consequently, on the supply side, banks and lenders, in general, are typically not willing to lend capital to small companies, while on the demand side nascent small firms are off the market (Ang, 1992).

The evaluation of an entrepreneurial project is a cognitive activity. Like any other type of assessment, this activity requires an affirmative or negative decision about what is being evaluated. Any cognitive action involves information processing. However, complete information about entrepreneurial projects is hardly ever available, and for that reason, evaluators —banks, agencies, venture capitalists, and angel investors — search for signals for assessing entrepreneurial projects, because they need cognitive heuristics and shortcuts to process high amounts of incomplete and asymmetric information. These signals are reviewed in more detail in the next section and help in developing the hypotheses of this study.

2.2 Factors associated with entrepreneurial funding

Some factors associated with external funding are related to an entrepreneur's economic and social status, while others to the specific actions of an entrepreneur for acquiring funding. Among economic and social factors, a primary driver for acquiring external funding an entrepreneur wealth. Even the decision to become an entrepreneur is subject to an individual’s net worth capacity (Evans and Jovanovic, 1989). Frid, Wyman, Gartner, and Hechevarría (2016) found that personal wealth is a primary driver for acquiring external startup financing. Also, low-wealth entrepreneurs are less likely to get external funding, and even when they do so, they receive lower amounts compared to wealthier entrepreneurs (Frid, Wyman, Gartner, and Hechevarría, 2016; Frid, Wyman, and Coffey, 2016; Frid, 2014; Reynolds, 2011). Frid, Wyman, Gartner, and Hechevarría (2016) observed the impact of the wealth of an entrepreneur on venture creation and performance during its gestational phase (Reynolds and Curtin, 2008). They found that low wealth and moderately wealthy nascent entrepreneurs face liquidity constraints, influencing the performance of the new ventures. Consequently, low and moderately wealth entrepreneurs are more likely to abandon the startup process during the gestation period. However, once low and middle wealth entrepreneurs pass that phase, their likelihood of deserting is similar to the wealthy entrepreneurs. Therefore, and as Frid Wyman, Gartner, and Hechevarría (2016) point out, low and middle-wealth entrepreneurs face liquidity constraints, but they are as capable as wealthier entrepreneurs once they pass the financial constraints of the gestational phase. Thus, personal wealth is a crucial factor in obtaining external funding recursively due to two reasons: first, its positive relationship with external funding and on second extending the gestational phase, which is the period when NEs could get external funding. Therefore, the first hypothesis is:

H1: *Less wealthy nascent entrepreneurs will be less likely to acquire external funds recurrently than wealthier business founders.*

A similar logic applies to social capital. Entrepreneurs' career trajectories have a remarkable impact on their firm’s growth, as shown by Burton, Sørensen, and Beckman (2002). The accumulation of social capital facilitates access to information and tangible resources such as credit and financing tools. Uzzi (1999) found in his study on existing firms, "the ability to meet financial selection criteria is a product of a firm's characteristics as well as the socially arranged opportunity structures within which it is embedded. Firms with embedded relations and high networks complementarity are more likely to be deemed credit eligible and to receive lower cost financing (…) Thus, market-making –or the creation of exchanges for mutual benefit– depends on social relations and networks." (Uzzi; 1999, 502).

While there is no difference in the amount of social capital between entrepreneurs and the general population, the formers use it differently: entrepreneurs are more skillful in taking advantage of their connections and ties (Liao and Welsch, 2005). As mentioned, low-wealth entrepreneurs are less likely to get funded compared then wealthier entrepreneurs, as Casey (2014) demonstrated, the support provided by community-based organizations increases their credit access. As social capital seems to affect the quality and results of an entrepreneur's ability to get funded, it is hypothesized that

H2: *Entrepreneurs with higher levels of social capital are more likely to obtain external funding recurrently.*

In addition, there are also factors associated with receiving funding based on an entrepreneur's actions, and not from here social or economic origin. NEs can reduce the asymmetrical information and transaction costs by developing signals for lenders, such as business plans, patents, or financial projections. Entrepreneurs that develop business plans receive higher funding amounts (Hopp, 2015) because such plans are associated with persistence in the process of business creation (Liao and Gartner, 2006). Kirsch, Goldfarb, and Gera (2009) indicate that business plans have a critical purpose in entrepreneurship, namely the role of acquiring a costly signal. Honig and Karlsson (2004) also affirm that business plans are legitimation devices which communicate to investors that entrepreneurs understand the rules of the game but reveal little to none about their abilities. Scholars have pointed out that business planning reduces entrepreneurial uncertainty. Liao and Gartner (2006) found that pre-venture planning increases the chances of emerging firm persistence in high uncertainty contexts. For those NEs who are confident about their competitive and financial situation, planning is less relevant. Also, Liao and Gartner (2006) found that business planning significantly increases the likelihood of firm creation and persistence. Brinckmann and Sung Ming (2015) also show that NEs look for external financing develop business planning activities, and finding that education helps them to engage in business planning activities and formally set up business plans. In contrast, prior work experience has a weak effect on developing business plans.

As signals for obtaining funding, financial projections have been the focus of research less than business plans. However, there is evidence that entrepreneurs develop them more often when their new venture operates in markets where intangible assets such as patents or R&D spending are critical to reducing uncertainty (Cassar, 2009). Also, patents infer reputation for NEs' (Hsu, 2004; Lounsbury and Glynn, 2001). Funders interested in high-tech new ventures look for evidence of NEs' prior accomplishments, like patents (D. H. Hsu, 2007). Thus, a set of hypotheses is proposed to test how these signals affect NEs' recursive financing:

H3a: *Nascent entrepreneurs who develop business plans are more likely to receive external funding recurrently.*

H3b: *Nascent entrepreneurs who develop financial projections are more likely to receive external funding recurrently.*

H3c: *Nascent entrepreneurs who develop patents are more likely to receive external funding recurrently.*

2.3 Effects of recurrent external monitored funding

Behind the idea of a potential Matthew effect in entrepreneurial financing, there is an underlying hypothesis: Receiving externally monitored funding several times provides an advantage to NEs in their goal of creating a new firm. Frid (2014) and Gartner, Frid and Alexander (2012) studied new companies' capital structure in the nascent context, demonstrating that NEs tend to use personal funds as the primary funding source during the earliest stages of the entrepreneurial process. Hecheverria *et al*. (2016) challenged these findings by using event history analysis and confirming that a capital structure that contains external funds (equity) is positively associated with accelerating new firm creation during the gestational phase. They also found that firms with a capital structure that contains external loans and equity are less likely to disengage from the entrepreneurial process. They suggest that external sources of capital could add more value to investee firms than private money from savings. As a result, there appears to be a relationship between a firm's capital structure and external funds, with firm creation and survival. Thus, receiving external funding recursively during the early stages could accelerate firm creation and reduce disengagement, because acquiring these funds steadily during the gestational phase can increase the share of external funds in the capital structure new venture. Therefore, the underlying hypotheses are;

H0a*: Receiving monitored external funding several times extends firm survival*

H0b*: Receiving monitored external funding several times accelerates firm creation*

3. METHODS

Receiving external funding can happen several times during a new venture's gestational phase. Thus, time is a central dimension for this research reported here, and longitudinal studies offer the appropriate data structures to follow NEs through time. The Panel Study of Entrepreneurial Dynamics (PSED) is a representative longitudinal sample of individuals attempting to start businesses in the U.S. PSED offers substantial research advantages, such as avoiding the biases found in other longitudinal studies for entrepreneurship, such as the survivorship and the recall biases. The former happens when the study gathers information about operating ventures and not for those that disengage during the period of study, while the latter occurs when surveying established entrepreneurs about past events (Gartner *et al*., 2004). The PSED-I and II datasets are the primary sources used in this study

3.1 Sample

The sample in this study resulted from matching PSED-I, II, and the PSED harmonized transitions database. PSED-I and II offer a representative and a publicly available[14] sample of NEs at the U.S. scale focused on the business formation process. This study provides data on new venture founders on the timing to create a new firm or to disengage from the start-up process (Gartner and Shaver, 2012). To be considered a NE during the screening process, the respondent had to answer that:

a) “[they] considered themselves in the firm creation process;

b) [they] had been engaged in some behavior to implement a new firm—such as having sought a bank loan, prepared a business plan, looked for a business location, or taken other similar actions;

c) [they] expected to own part of the new venture;

d) the new venture had not yet become an operating business” (Reynolds and Curtin, 2008, p. 172).

[14] Access for PSED-I, PSED-II and the consolidated data set can be found at www.psed.isr.umich.edu

Based on these screening questions, 830 and 1214 individuals were selected for the samples of PSED-I and PSED-II, respectively. PSED-I has a maximum of four waves for each entrepreneur collected between 1999 and 2003, while PSED-II consists of a maximum of six waves for each case, collected between 2005 and 2012.

Matching PSED-I and II resulted in 2044 cases. However, only those categorized as "good cases"[15] (1599 entrepreneurs) in the PSED harmonized transition dataset were considered. From those cases, 41 were removed due to the lack of information about household net-worth as other 26 cases because their conception dates were defined after the first interview, adding another period of observation (before gestation) for those cases which was not of interest for this study (see Figure 1). As a result, 1532 cases are under analysis for this research.

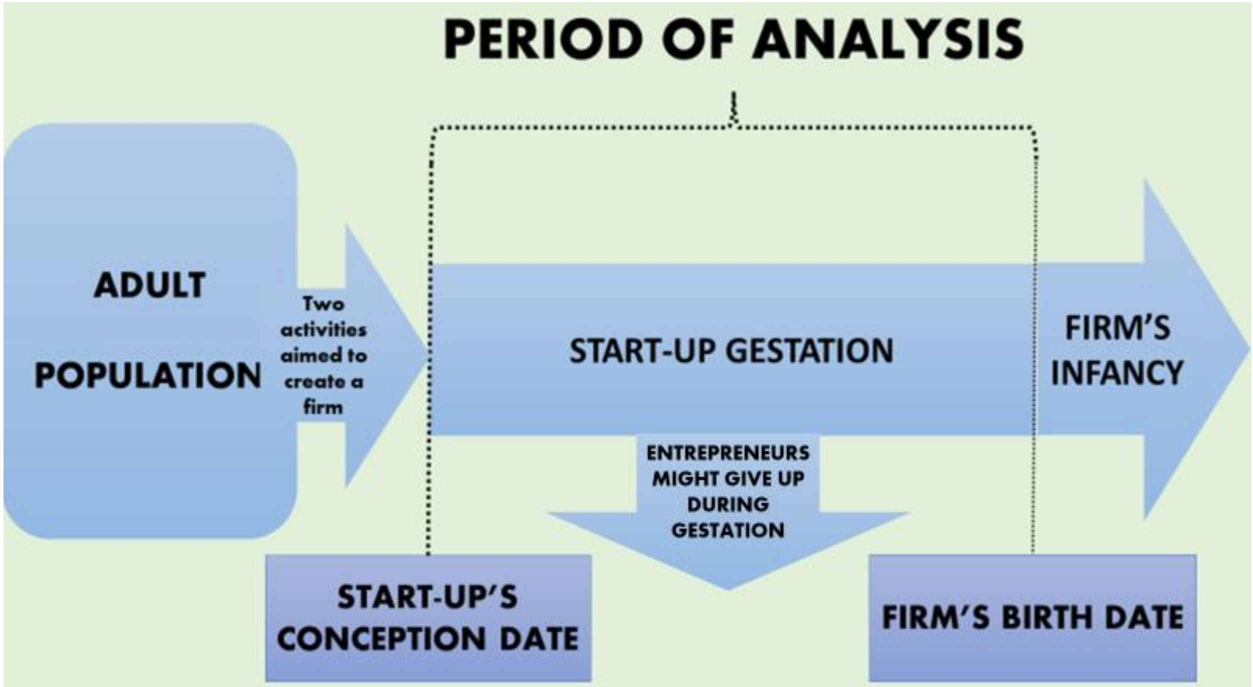
The period under observation was the entrepreneurial gestational phase. Gestation starts when conception, and it is completed when NEs disengage from creating the new firm or when it is finally created. More specifically, conception takes place when two intended activities aimed to create a firm[16] has have been taken within a twelve-month window[17] (Reynolds and Curtin, 2008, 2011). Figure 1, based on the work of Reynolds, Gartner, Greene, Cox, and Carter (2008), describes the entrepreneurship process under the PSED framework, highlighting the gestational phase in it (Reynolds, 2017; Reynolds and Curtin, 2008; Reynolds, Carter, Gartner, and Greene, 2004).

[15] "Good cases" are those qualified as active nascent entrepreneurs for which there are one or more follow-up interviews

[16] These possible startup activities are: Invested own money; Began business plan Developed model, prototype; Purchased materials, supplies, parts; Define markets to enter; Promote products or services; Sales, income, or revenue; Leased, acquired major assets; Talk to customers; Financial projections; Full time start-up work; Saving money to invest in firm; Phone book listing for business; Established bank account for firm; Obtained supplier credit; Began to organize start-up team; First use of physical space; Hire lawyer; Business plan finished; Model, prototype fully developed; Signed ownership agreement; Proprietary technology developed; Invested own money; Investment in legal business; Know listed in Dun and Bradstreet; Signed ownership agreement; Full-time start-up work; Invested own money; Received patent, copyright, trademark; Signed ownership agreement; Signed ownership agreement; Invested own money; Full time start-up work; Signed ownership agreement; Invested own money; Full time start-up work; Full time start-up work. Serious thought on starting a company it is an activity asked, but it is not considered to start or end counting gestations since virtually all entrepreneurs mentioned it. (from Reynolds, 2017)

[17] The specific date that defines gestation is the first of the two activities within the 12 months period.

Figure 1 - Conceptualization of the entrepreneurial process period



During the gestational phase, the startup's creation or disengagement from the entrepreneurial process can occur. The definitions of startup creation and disengagement are defined in section 3.2.1.

3.2 Variables

3.2.1 Dependent variables

When the objective is to analyze the time-to-events, there is a need for using an event indicator and either time-to-event or time-to-censoring measurement. Based on the hypotheses of this research, there are several time-to-event variables modeled: firm creation, survival, receiving external monitored funding, or duration of gestation period until none of these events happens (censoring). Time begins with the startup's conception date, and it is measured as the number of months-to-event or months-to-censoring.

The event indicator changes depending on the model evaluated. The first model tests the underlying hypotheses, whether the recurrent reception of monitored funding matters for firm survival. In this case, disengaging from the gestational phase occurs when an entrepreneur reports that no one is managing the startup anymore. The second model tests whether receiving monitored funding several times affects firm creation. In this case, the event occurs when the entrepreneur reports start-up profits for the first time, defined as positive month cash flow for six of the past twelve months in PSED-II and three of the past twelve months in PSED-I (Reynolds and Curtin, 2008). Those cases that have not reached a resolution (firm's disengagement or creation) after the observation period constitute entrepreneurs labeled as "still trying" and will be the right-censored cases.

After evaluating the effects of recurrent monitored funding, this research aimed to understand the factors associated with receiving it. For that exercise, the event is receiving external monitored funding (REMF). The definition of external monitored funding used in this research is the same applied by (William B. Gartner, Frid, Alexander, & Carter, 2009a), in other studies done using PSED datasets (Frid, Wyman, Gartner, and Hechavarria, 2016; Frid, 2014). Virtually all entrepreneurs use personal and other team members' funds to invest in their projects. However, in terms of acquiring funds from external sources, Gartner *et al.* (2009) note that two categories emerge with different levels of oversight and involvement: unmonitored and monitored funding sources. If the former includes funding coming from family members, friends, second mortgage, or credit cards. These sources are not strictly monitored in terms of how the funds are or will be used.

In contrast, monitored sources include bank or finance company loans, Small Business Administration credit, venture capital, and credit coming from a current employer granted after a thorough understanding of the business or financial plan. In those cases, NEs must provide some indication of how they are planning to use these funds or, in case of loans, when they will be paid back. Also, this type of funding can be subject to governmental policy, through public funding or through programs to foster and facilitate loans for NEs. Thus, receiving externally monitored funding (REMF) is the third event of interest.

Since there is no exact date associated with REMF in PSED, it is approximated using the time from conception to the first interview when the entrepreneur reported receiving its first externally monitored fund. The subsequent REMF events are the time-gaps in months between the interviews that the entrepreneur reported receiving externally monitored funds. The PSED interviews usually were conducted approximately every 12 months[18] for each entrepreneur (Appendix E). This date is the most effective and accurate approximation of the time of receipt of external funding. In the case of models explaining externally monitored funding, censoring defines for those companies that have either disengaged, created the company, or have never received externally monitored funding during the period of observation.

3.2.2 Independent variables

3.2.2.1 Firm survival and creation models

The effects of REMF on firm creation and survival are analyzed by developing a similar model that Hechavarría *et al*. (2016) applied to understand the effect of funding sources (equity and debt) on the same dependent variables used here. With some adjustments adapted to the questions of this study, virtually the same variables that Hecheverria *et al*. (2016) used are included here, but letting them vary with time. This study included funding times, a categorical variable that measures whether the startup has not received any external monitored funding (=0), has received

[18] While there are some extreme observations, most cases have time-gaps around 12 months between PSED interviews. That is possible to be seen in the average time as well as the median time between interviews available in Appendix A.

it once (=1), has received least twice (=2). This variable aims to test hypotheses 0a and 0b, the effect of REMF on firm survival and creation.[19]

Wealth impacts the probability of disengaging from the entrepreneurial process (Frid, Wyman, and Coffey, 2016; Frid, Wyman, Gartner, and Hechavarria, 2016). For that reason, the entrepreneur's household net-worth is included. Values were standardized using 2005 prices based on the recommendations of Reynolds and Curtin (2008). Since this variable was asked only for the first PSED interview, it is not time-dependent and accounts only for the respondent's household net worth. The size of the organization influences the disengagement from the start-up process, as Carroll and Hannan (2000) demonstrated. For this reason, a time-varying variable that measures the number of start-up owners (individuals or organizations) for each PSED wave is included. The variable sweat equity accounts for the team's total hours of work on the startup, for each PSED interview.

The number of men on the start-up team (owners) is also included females start smaller businesses compared to males (Fairlie and Robb, 2009). There are also links between motivations and aspirations to become entrepreneurs based on race: whites are more internally motivated and have higher expectations to become entrepreneurs, and on the other hand, unemployment and low wages motivate African-Americans to start new companies (Sabbaghi, 2018; Singh, Know, and Crump, 2008). Thus, the number of men on the startup team is included to account for the former, and the number of Caucasians on the startup for the latter. Because these variables can vary with time, both are time-varying variables for each PSED wave available. Entrepreneurs' age is an essential factor for start-up survival and creation. Hechavarría *et al*. (2016) used five variables to control for the number of members on the start-up teams age between 18-24, 25–34, 35–44, 45–

[19] It could have been possible to create a variable that measures the number of all funding events, but the second category was restricted to two or more to avoid the possible correlation with the time that a counting variable of funding events can have.

54, and 55–99 and the same variables were applied in this study. These variables vary with time, depending on the number of owners within each age-range[20].

Entrepreneur's growth preference is a dummy variable that accounts for entrepreneurs' over-optimistic tendencies, leading them to underestimate competition and overestimate growth aspirations (Delmar and Shane, 2003). Startup's degree of innovativeness is a categorical variable ranging from 0 to 3. This variable is categorized 0 when the (a) entrepreneur reports that the products and services are not a novelty[21], (b) their report the decision to not spending funds on R&D, and (c) report that their new venture is not hi-tech. When the entrepreneurs affirm one of these three categories, the degree of innovativeness is labeled 1. This variable is categorized 2 when the entrepreneur reports at least two of these and 3 when all of them were affirmed.

A business plan is associated with persistence in the entrepreneurial process, especially if entrepreneurs develop them one during the early stages (Liao and Gartner, 2006). Thus, a control for having a plan or not, and for the type of business plan for each PSED wave is included. This variable is categorical ranged from 0 to 3, and it is labeled 0 when the entrepreneurs did not develop a business plan, 1 when they have an unwritten plan, 2 when they have an informal plan, and 3 when they developed a formal written plan. Financial projections reduce uncertainty in highly uncertain markets (Cassar, 2009); thus, this time-varying variable is included, and it is labeled 1 when the entrepreneur report having financial projections in a specific PSED interview and 0 otherwise. Team industry experience is a variable that measures the number of years of experience in the same industry of the startup for each owner. It is an aggregate of each owners' years of experience, and it is also time-varying. Based on the positive attitudes that can emerge towards

[20] Unfortunately, PSED I asked age only for the five more important owners; thus, when one of these variables is "5" it means that there are five or more startup owners within that range. However, less than 0.05% of total PSED-I observations declared having more than 5 owners. In the case of PSED II, this number increases to 1.06%.
[21] This category measures if products or services to be provided by the new venture were available five years ago

entrepreneurship due to previous exposure to it (McCann, 2017), the number of *prior start-up attempts* is also a time-varying variable, accounting for the number of former startups that each team member individually intended. Since PSED-I contains only the respondent's educational level, it is measured using a categorical variable that accounts for only the respondents' level and not the entire team. This variable uses 0 as base if the entrepreneur has a high school degree or less; tech, community, or some college = 1, college or some graduate training = 2, master's degree =3, or Ph.D. degree = 4.

A categorical variable start-up principal economic activity is included to control for the effects of the economic sector. This variable equals 0 when the startup expects to operate in the business service market, 1 in the extractive sector, 2 in transforming sectors, =3 in consumer-oriented sectors, and 4 for other sectors/NA. Also, total funds in logs are included regardless of the source secured by the start-up team. Gartner, Frid, and Alexander (2012) demonstrated that NE uses their funds as the primary source of funding during the early gestational phase and as these individuals advance in the process, their likelihood of acquiring external sources of debt and equity increases. Therefore, a time-varying variable that accounts for the percentage of personal funds on start-up total funding is included. Also, a time-varying variable is used, measuring the unmonitored external funds as a percentage of total startup funding. Lastly, conception lag is included based on the recommendation of Yang and Aldrich (2012) to account for left truncation when evaluating firm survival and creation using PSED. This variable accounts for the time in months of the first interview minus the conception date in months. This variable was interacted with time to account for the proportional hazard assumption of the Cox regression model (Cox, 1972), described in Section 4.

3.2.2.2 Recursive funding models

As a second step after analyzing firm survival and creation using Cox regression models, the goal will be to test hypotheses 1, 2, and 3a, b, and c. To meet these objectives, a set of standard and conditional frailty models (explained in the next section) are applied. One of the most cited articles aimed to understand the effects of social and economic origin on receiving funding grants using PSED is the article of Frid, Wyman, Gartner, and Hechavarría (2016). Receiving "funding" can happen several times, making it a potential repeated event. For that reason, the models used in this paper differ from those applied in Frid, Wyman, and Coffey (2016). The same variables utilized in Frid, Wyman, Gartner, and Hechavarría (2016) were included, to have a threshold to compare with, adding the specific variables to test the hypotheses of this paper.

Some variables already described are also used for these models. These variables are conception lag, type of business, level of education variables, number of team's prior start-up attempts, the number of white/caucasians in team, the number of men in team, percentage of personal funding in total funding, and the age-range variables. Household net worth was divided into tertiles to test hypothesis 1. If it is addressed linearly using a continuous variable, it will be possible to know how an additional dollar of net-worth affects receiving funding. However, and taking into account that information is lost when a continuous variable is transformed into a categorical one (Osborne, 2017b), testing a continuous variable adds no value to test the hypothesis of this study. Using a continuous variable will not help in the objective to know how the wealthier performs against the non-wealthy. Also, it will not reveal at which threshold net-worth becomes explicative of receiving external monitored funding. The option of dividing house-hold net-worth into three equal percentiles was done following Frid, Wyman, and Coffey's (2016) study, which addressed a similar issue using tertiles.

In entrepreneurship studies, scholars have measured social capital using different approaches. Casey (2014) used years of industry experience, and years of management experience, as proxies for social capital. It is well-known from the literature that entrepreneurs with senior management experience are perceived as being stronger candidates by third parties, making them more likely to obtain external funding (Burton *et al.*, 2002). Therefore, team managerial experience (in years) measures a status-based social capital. Regarding industry experience, Hellmann and Puri (2002) found that teams with relevant experience in a specific industry are aware of critical resources and key individuals in that domain.

It is important to highlight that industry experience has been linked with entrepreneurs' human capital, as well. Previous work experience in the same industry can help entrepreneurs in enhancing their tacit knowledge on different dimensions, especially about how to interpret information, and then perceive and evaluate opportunities in the economic sector within which they aim to operate (Muñoz-Bullon, Sanchez-Bueno, and Vos-Saz, 2015; Shane, 2000). While recognizing the former, for the goal of this research, which is to investigate the entrepreneur's access to external funding, it is more important to consider the social capital side of industry experience. That is because industry experience operates connecting entrepreneurs to funding networks that may otherwise not be available, or signal lower risk to outside investors, as argued by Gartner *et al*. (2012). Thus, industry experience is interpreted here as a status-based social capital as well. Therefore, team industry experience (years) in the start-up economic sector is measured as described in the previous section, but it is entered squared since Frid, Wyman, Gartner, and Hechevarría (2016) found a curvilinear relationship between this variable and receiving external funding.

Additionally, Newbert and Tornikoski (2012) quantified entrepreneurs' social capital through its networks measuring a specific number of individuals, who have provided resources to the emerging organization and are not part of the start-up team. To properly evaluate the data, family and friends were removed to ensure that strong ties will not be related to the weak ties that can provide an emerging firm with new resources. This approach relies on Granovetter's (1985) distinction between strong and weak ties (bonding and bridging social capital). Strong ties involve significant investments of time and energy, whereas weak ties are acquaintances. Strong ties may help gain access to emotional support and assistance in the case of emergencies. Weak ties may especially aid in finding assets (Green and Haines, 2008). It is through weak ties that entrepreneurs can exploit social capital. Based on the previous, a numeric variable, social capital – bridging, will count numbers of non-family and non-friend helpers, aiming to measure the concrete entrepreneurs' network. Social capital – bonding is another control variable that measures the number of non-owner family helpers. Table 1 simplifies the social capital concepts and variables used in this research.

Table 1- Social capital concept, variables, and previous research

Social capital concept	***Variables applied***	***Previous PSED research that applied the concepty***
Status-based social capital	Team's managerial experience (years) Team's Industry experience (years)	Casey (2014)
Network-based social capital	Bridging social capital (numberf of people)	Newbert an Tornikoski (2012)

Regarding hypothesis 3a, 3b, and 3c, the aim is testing three signals that might reduce asymmetrical information. A business plan is measured as described previously, as well as financial projection. Regarding patents, they are placed into the same question as other signals: the specific question is: *"there are trademarks, and copyrights (as well as patents) granted for the* *new venture?"*. Thus, the variable patents, trademarks, and copyrights granted will = 1 when the entrepreneurs answered "yes" to the last question, otherwise is coded = 0.

Following Frid, Wyman, Gartner, and Hechavarría (2016), this study includes another set of control variables. Startups located in or near a metropolitan area have more opportunities to acquire formal, external financing compared to those in rural zones. Thus, a dummy variable, *new venture in metropolitan area* will be coded = 1 when the startup is located in metro areas, otherwise will be coded 0. The *start-up legal form* coded as 0 = sole- proprietorship (base); 1=partnership; 2=limited liability company; 3=C- or S-corporation; and 4=not yet determined; 5=other. Startup type codes are 0= independent new venture; 1=takeover of existing business; 2=franchise; 3=multilevel marketing initiative; and 4=startup sponsored by an existing business[22].

3.3 Models

The first objective of this study is the impact of REMF on event occurrence while controlling for a wide range of fixed and time-varying covariates, using a similar model as Hechavarría's *et al*. (2016). The event of interest is exiting the gestational phase via either new firm creation or giving up the intention to do so. Previous efforts exploring external funding during startup gestation did not use event history analysis techniques and, therefore, did not account for censoring (Frid, 2014; Gartner e*t al.*, 2012). Consequently, this research uses event history analysis and employed two Cox proportional hazards regressions (Cox, 1972) to investigate, if receiving funding more than one-time impacts positively on either firm survival or firm creation.

Based on Allison (2014), the modeling strategy is as follows. The probability that an entrepreneur experiences firm creation in the interval from t to $t + s$, given that the entrepreneur was at "risk" at time t, is denoted $P(t, t + s)$. This probability is divided by s, which is the length

[22] Procedures in R-script for variable construction and models can be provided by contacting the author.

of the time interval, and if *s* become smaller until the ratio reaches a specified limit, it is defined as the continuous-time hazard, denoted by $\lambda(t)$, formally

$$\lambda(t) = \lim_{s \to 0} \frac{P(t, t+s)}{s}$$

A basic Cox regression model aims to explain the continuous-time hazard for subject *i* as formally defined

$$\lambda_i(t) = \lambda_0(t) e^{X_i \beta + X_i + \delta}$$

where the baseline hazard function λ_0 is unspecified, is interpreted as the hazard function for subject *i* whose covariates all have the value of zero. Consequently, Cox models do not have an intercept term. The second part of the equation shows a linear function of an exponentiated set of β covariates, some of them fixed and others time-varying. The δ coefficient is the categorical variable external monitored funding times aimed to test Hypothesis 0.

A different model set that accounts for the repeated nature of receiving external monitored funding was developed to explore associated with recurrent financing. Since REMF allowances can occur more than one time during the gestational phase, a methodological approach designed to explain repeated events is needed. If the repeated nature of a potential recurrent event is taken into account, estimators can be biased (Amorim and Cai, 2015; Allison, 2014; Mills, 2014; Twisk, Smidt, and De Vente, 2005). The Cox model is both biased and inefficient in typical repeated event problems due to the correlation among events. Using a simple Cox model in for addressing repeated events violate the assumption that events are independent (Box-Steffensmeier and De Boef, 2006).

There are several advantages of using recurrent event models; addressing heterogeneity issues is being the most prominent. In addition, some NEs can be “frailer” than others. For example, they have different levels of information about funding sources, how to complete forms, the funding process in general, and other unobservable characteristics that make some NEs more likely to receive external monitored funding. When there is heterogeneous susceptibility to the risk of recurrent events, the frailty model must be applied (Amorim and Cai, 2015).

Frailty models incorporate heterogeneity into the estimator by making assumptions about the frailty distribution and including it in the model estimates. The underlying logic of frailty models for the research questions explored here is that some entrepreneurs are inherently more or less likely to obtain REMF than others, and the distribution of these effects can be approximated. Frailty models treat repeated events as a particular case of more general unit-level heterogeneity. In this case, the random effect is across entrepreneurs and constant over time, as seen in the formula below

$$\lambda_i(t) = \lambda_0(t - t_{k-1})e^{X_{ik}\nu + X_{ik}\pi + X_{ik}\rho + X_i\beta + \omega_i}$$

where X_i is the *ith* row of a covariate matrix X. The frailty model incorporates a random effect ω to the Cox regression equation that represents the subgroup for individual frailties, assumed to be an independent sample of a distribution with a mean 0 and a variance of 1. The term $(t - t_{k-1})$ accounts for the gap time structure, meaning the hazard gives the risk for event k since the previous event occurred. β gives the effect parameters of the control variables, while ρ, π, and ν, the effect of wealth, social capital, and signals parameters to test Hypothesis 1-3c.

In addition, if it is reasonable to assume that the occurrence of an event affects its re-occurrence, a conditional frailty model can address this issue by letting the baseline hazard vary for each event (Box-Steffensmeier and De Boef, 2006). Therefore, a conditional frailty model was applied,

$$\lambda_{ik}(t) = \lambda_{0k}(t - t_{k-1})e^{X_{ik}\nu + X_{ik}\pi + X_{ik}\rho + X_i\beta + \omega_i}$$

where k denotes the event number; λ_{0k} is the baseline hazard rate that varies by event number k; $(t - t_{k-1})$ incorporates a gap time structure so that the hazard gives the risk for event k since the previous event occurred; X is a vector of independent variables which may be time-varying; and β gives the effect parameters, while the standard frailty model ρ, π, ν, parameters account for the effect of wealth, social capital, and signals for testing Hypothesis 1-3c. The remaining portion of the hazard incorporates the random effect. Each subject i has a random effect that is shared and constant over time (across events) and ω is a vector containing unknown frailties.

4. RESULTS

4.1 Firm survival and creation

In an event model, the dependent variable is composed of an event indicator and a measure of time from the baseline to the event or censoring. The disengagement from the entrepreneurial process and firm creation (births) are the first events of interest of this research. In the first case, the interest relies on those who do not disengage (survival). As seen in Table 2, on average, NEs take about 43 months to reach some outcome event, 26% of startups finally became a new firm, and 44% disengage from the entrepreneurial process in the observation period.

Table 2 – Descriptive Statistics, for firm survival and creation

	Firm creation and Survival Models	
	Mean	S.D.
Dependent variables		
Time months	43.29	31.12
Firm birth	0.26	0.44
Disengagement from the entrepreneurial process	0.41	0.49
Independent variables		
Times received external monitored funding	0.31	0.62
Demographic controls		
Education	1.42	1.04
Number of men in the team	0.89	0.94
Number of white/Caucasians in team	1.34	1.25
Total number of under 24 years old team members	0.12	0.45
Total number of 25-34 years old team members	0.32	0.65
Total number of 35-44 years old team members	0.44	0.68
Total number of 45-54 years old team members	0.45	0.66
Total number of above 54 years old team members	0.38	0.69
Entrepreneurs' experience and intentions controls		
Team industry experience in the start-up economic sector (years)	14.75	16.36
Number of team's prior start-up attempts	1.87	3.87
Growth preference dummy, "as large as possible" =1	0.22	0.41
Startup characteristics controls		
Number of people or institutions that owns the start-up	1.86	2.81
Degree of innovativeness	0.81	0.90
Business plan	0.79	1.12
Financial projections, "have developed financial projections" = 1	0.20	0.40
Type of business	1.37	1.34
Financial controls		
Household net worth, 2005 prices	803,281	7645779
Personal funding / total funding	44.18	45.21
Unmonitored external funding / total funding	10.24	23.21
Total startup funding (log)	5.49	4.82
Team's sweat equity (total hours)	2610	6381
Other controls		
Conception lag	33.07	28.40

In this research, the key independent variable of interest when evaluating firm survival and creation how many times it was funded during the entrepreneurial process. Receiving monitored external funding show a mean value of 0.31, meaning that most of the firms did not receive any external monitored funding. External funding is not the most common source of funding for entrepreneurs, and as it is known from the work of Frid (2014) that most of the entrepreneurs use their funds as the principal source of funding.

One of the advantages of this research is the wide range of control variables applied (21). These variables ranged from entrepreneurs' demographic variables, their trajectories and future intentions regarding the startup, its characteristics, and the entrepreneurs' financial origin and investments. Among the demographic characteristics of the entrepreneurs, on average, they are educated, work in small teams, are males within 35- and 54 years old, and are from Caucasian ethnicity. Specifically, it is worth noting that most founding teams have at least a college degree since the education mean is 1.42. Entrepreneurs tend to work together ins small teams since on average, the number of people or institutions that owns the start-up is 1.8. Also, the average number of males on the startups of this sample is 0.9, meaning that in most entrepreneurial teams it is possible to find at least one male member. Also, most start-ups have one person of Caucasian ethnicity, because the mean is above 1 (1=Caucasian). Regarding age, 35–44 and 45–54 years of age are the most common age ranges for start-up team members.

Regarding entrepreneurial trajectories and intentions, entrepreneurs are experienced in their economic sector, have intended to create companies before, and do not show high aspirations in terms of their startup growth. As seen in Table 2, founding teams shows a mean of 14.7 years of industry experience and have, on average, engaged in 1.8 start-ups. Most entrepreneurs (78%) want to create a new company that is easy to manage, and only 22% of entrepreneurs want to maximize the growth of their startups.

Entrepreneurs create startups that are not technologically sophisticated on average. Also, they do not prepare their business using a business plan nor financial projections and aim to operate in the service sector. The degree of innovativeness accounts for an average of 0.81, which indicates that the vast majority do not aspire to offer new products or services and do not invest in R&D. Most of the entrepreneurs indicate they do not have a business plan, since the mean is 0.79, and only 20% have completed financial projections. A mean of 1.3 in the type of business informs that the majority operates in the business services sector. The distribution of this variable shows that 43% of startups will do business in the business services sector (base category), 4% in the extractive activities, 19% in transforming industries, 33% in consumer-oriented sectors, and 1% in other activities.

Financially, most of the entrepreneurs in this study are economically affluent, tend to use their funds for financing the startup instead of unmonitored external funds, and spent working a high number of hours on them. Specifically, the average household net worth in the sample is approximately $803,200[23]. and the percentage of personal funds on the total startup funding average is 44.18, meaning, as previous studies identified as well, that it is the most used funding source for startups compared to unmonitored external funding, which is on average only 10.24. The average amount of total funds (in logs) invested in the startup is 5.49, which is around $100.000, while the total working hours on the startup for teams is 2610.

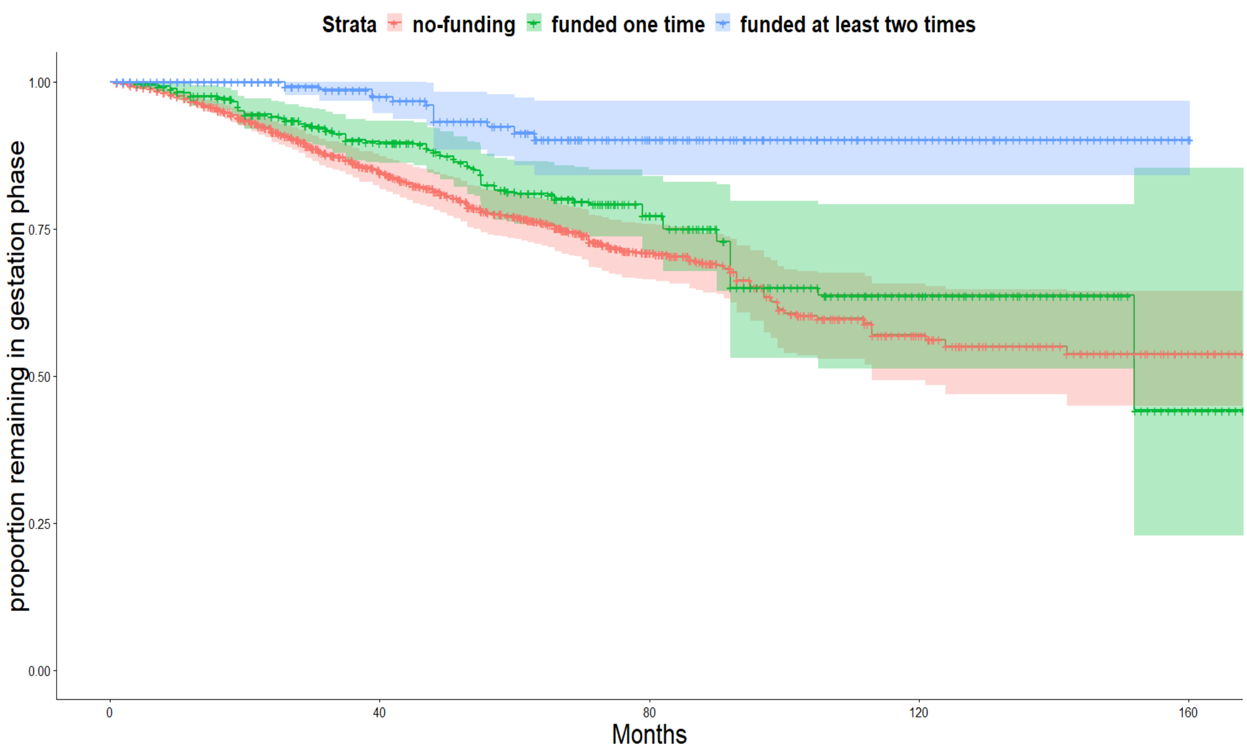
Hypotheses 0A and 0B were tested by fitting two Cox-regressions (Cox, 1972). For the analyses, the statistical models were performed using R packages survival (Therneau and Lumley, 2015) and survminer (Kassambara, Marcin, Przemyslaw, and Scheipl, 2018). Using the *surv* command, this set of regressions analyzed data from the 1532 NEs. First, a Cox regression was fit using the firm disengagement from the entrepreneurial process as the event of interest. Next, a Cox regression using firm creation as the event investigated. In both models, cases that are still trying to create the firm are right-censored. To analyze time-varying variables, the dataset was transformed from wide to long format using the survSplit function of the survival R package. After

[23] The trimmed mean (0.025 for each distribution side) is around 245000, meaning that few households are accounting for a high net worth influencing on the mean results.

this transformation, each row represents an entrepreneur's specific month during the gestational phase until an event happens.

In this sample, 406 cases reached new firm status, 630 were disengaged, and 495 are censored (still trying). Figure 2 presents Kaplan-Meier estimates for those new ventures in the still-trying phase. The analysis focused on parameter δ, which estimates the effect of a categorical variable aimed to measure how many times startups received external monitored funds. In Figure 2, the number 1 represents the total startups, and any reduction from 1 means a startup that disengaged from the entrepreneurial process. Based on these estimates, 90% of startups that receive funding at least two times (blue line) do not disengage from the entrepreneurial process during the period of observation. Interestingly, startups that received external funding one time (green line) disengage in similar numbers to those that have never receive external monitored funding (red line).

Figure 2 – Kaplan-Maier estimates for firm survival, stratified by the number of external monitored funding received



The survival function of startups that receive funding one time and those that never received start to look very similar after 80 months of being in the entrepreneurial process. Therefore, it seems that all the benefits of being funded one time might have for firm survival disappear if the startup does not receive another monitored external funding before its first 80 operating months. This finding reinforces the central thesis of this study: receiving external monitored funding recurrently during the gestational phase is vital for startup survival.

Table 3 presents the empirical results. Model 1 evaluates firm survival. At least one of the covariates contributes significantly to the explanation of the duration of the events of interest. The likelihood-ratio chi-square statistic is the difference between -2 partial log-likelihood for the model with 36 covariates and the null model with no covariates. Since its p-value is <0.001, it is possible to reject the null hypothesis of the model's overall significance. The proportional hazard assumption implied in a cox model was met: Schoenfeld residual is >0.05. Since conception lag was not meeting this assumption in a previous model (not shown), an interaction was included between this variable and time, following as Allison, (2014) and Mills', (2014) recommendation, and therefore the proportional hazard assumption was met.

Table 3 – Cox Regression Models, firm survival and creation

	MODEL 1: Cox regression model (new venture disengagement)			MODEL 2: Cox regression model (new firm creation)		
	COEF	**SE**	**Exponentiated coefficient**	**COEF**	**SE**	**Exponentiated coefficient**
Funding: never received external monitored funding, base = 0						
Monitored external funding one time	-0.31*	-0.14	0.73*	0.1	-0.15	1.11
Monitored external funding at least two times	-1.22***	-0.34	0.30***	0.43*	-0.18	1.54*
Household net worth, 2005 prices	0.00*	0	1.00*	0	0	1.00
Number of people or institutions that owns the start-up	0	-0.01	1.00	-0.06	-0.06	0.94
Team's sweat equity (total hours)	-0.00*	0	1.00*	0	0	1.00
Number of men in team	0.01	-0.06	1.01	-0.02	-0.07	0.98
Number of white/caucasians in team	0.09*	-0.03	1.09*	0.05	-0.04	1.05
Total number of under 24 years old team members	-0.03	-0.1	0.97	0.17	-0.13	1.19
Total number of 25-34 years old team members	0.19**	-0.07	1.21**	0.19	-0.1	1.21
Total number of 35-44 years old team members	0.02	-0.08	1.02	0.12	-0.1	1.13
Total number of 45-54 years old team members	0.08	-0.08	1.08	0	-0.1	1.00
Total number of above 54 years old team members	-0.12	-0.08	0.89	0.03	-0.1	1.03
Growth preference dummy, "as large as possible" =1	0.16	-0.1	1.17	-0.28*	-0.13	0.76*
Degree of innovativeness, base = 0						
Degree of innovativeness 1	-0.09	-0.09	0.91	0.03	-0.12	1.03
Degree of innovativeness 2	-0.14	-0.12	0.87	0.24	-0.14	1.27
Degree of innovativeness 3	-0.09	-0.19	0.91	-0.28	-0.23	0.76
Business plan, base no business plan = 0						
Unwritten business plan	-0.08	-0.21	0.92	-0.13	-0.23	0.88
Informal business plan	-0.02	-0.16	0.98	0.32*	-0.14	1.38*
Formally written business plan	-0.49*	-0.21	0.61*	0.3	-0.17	1.35
Financial projections, "have developed financial projections" = 1	0.40**	-0.12	1.49**	-0.16	-0.14	0.85
Team industry experience in the start-up economic sector (years)	-0.01***	0	0.99***	0.01**	0	1.01**
Number of team's prior start-up attempts	0	-0.02	1.00	0.01	-0.01	1.01
Respondent education (base, high school degree or less)						
Tech, community, or some college	-0.23*	-0.11	0.79*	0.15	-0.14	1.16
College or some graduate training	-0.08	-0.11	0.92	0.02	-0.16	1.02
Master's degree	-0.32	-0.18	0.73	0.02	-0.21	1.02
PhD degree	-0.64*	-0.28	0.53*	0.14	-0.27	1.15
Start-up principal economic activity, base business services =0						
Extractive sector	0.1	-0.24	1.11	-0.57	-0.29	0.57
Transforming sectors	0.24*	-0.11	1.27*	0.36**	-0.13	1.43**
Consumer oriented sectors	0.11	-0.09	1.12	-0.01	-0.12	0.99
Other sectors/NA	0.02	-0.5	1.02	-0.77	-0.74	0.46
Total startup funding (log)	-0.11**	-0.04	0.90**	0.05*	-0.02	1.05*
Personal funding / total funding	-0.01**	0	0.99**	0	0	1.00
Unmonitored external funding / total funding	-0.01*	-0.01	0.99*	0	0	1.00
Conception lag	-0.06***	-0.01	0.94**	-0.04***	-0.01	0.96***
Conception lag*time	0.00***	0	1.00***	0.00***	0	1.00***
Likelihood ratio χ2	883.4***, on 35 df			166.6***, on 35 df		
Proportional Hazard test	0.61			0.30		

****p < 0.001, **p < 0.01, *p < 0.05*

By examining the hazard ratios in Model 1, specifically the exponentiated coefficients column reported in Table 3, it is possible to explore the nature of the relationship between variables and time to these events. If the estimated hazard ratio is greater than 1 for any variable of interest, higher levels of that covariate are associated with a higher incidence of disengagement, controlling for other variables in the model. For those firms that received externally monitored funding, results indicate the startup's hazard of disengagement is 73% of those startups that did not receive (p-value<0.05); start-ups which received monitored funding two or more times during gestation were revealed to be 30% of those that start-ups that did not receive any funding (p-value <0.001).

Other covariates of interest account for similar relationships found by Hechavarría *et al.* (2016). As mentioned previously, the main difference between the models of this study and those of Hecheverria *et al.* (2016) is the time-varying nature of many of the covariates added, with subsequent differences in results between the two studies. For example, holding all variables constant, each additional dollar of the entrepreneurs' household net worth slightly raises the likelihood of disengagement (0.000006%) while in Hechavarria *et al's.* model this variable was not significant to explain this event.

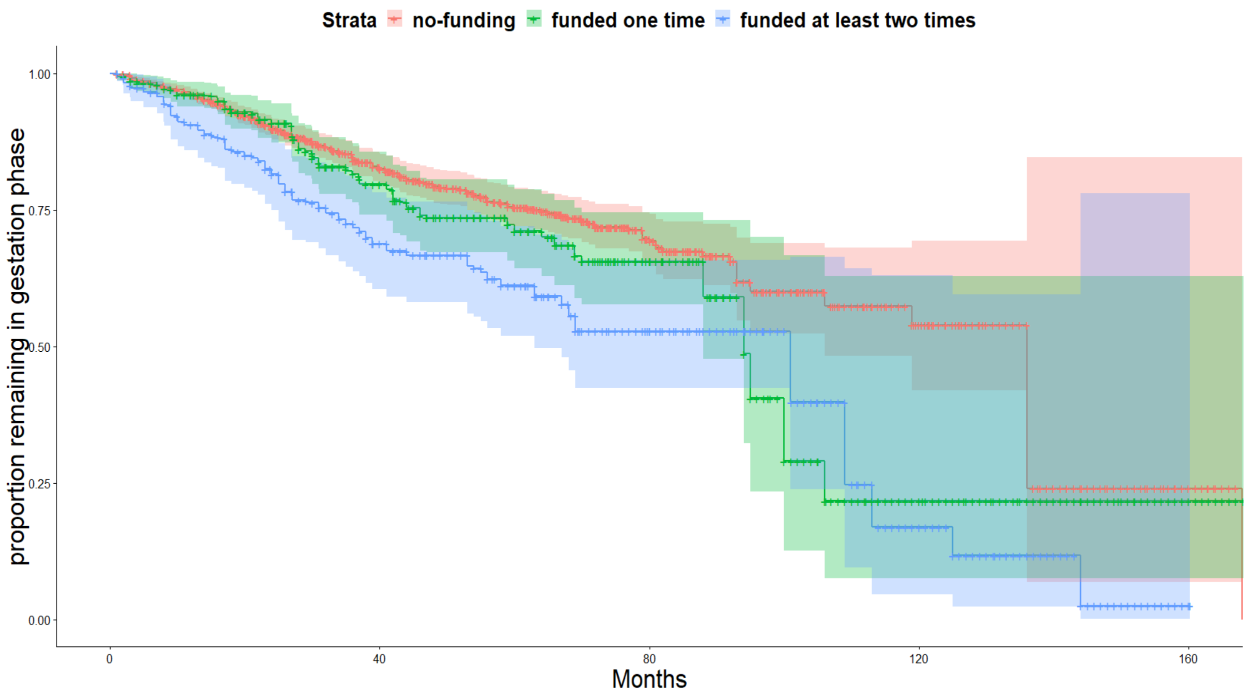
Sweat equity slightly reduces disengagement; for each additional hour of teamwork, the monthly hazard of disengagement decreases by 0.2%. Similarly, each additional Caucasian member on the start-up team reduces monthly disengagement from the gestational phase by 8.8%. As predictable, NEs whose business plan is formally written have a 21% hazard of disengagement compared to those without any business plan. Unexpectedly, the hazard ratio of disengagement of those entrepreneurs who have developed financial projections is 1.5 compared to those who have not developed one. For every team's year of industry experience in the same economic activity that the startup will operate, monthly disengagement hazard decreases by 1.3%. Respondent education accounts for an interesting association; the monthly disengagement hazard of those respondents who have a tech, community, or some college degree is 0.79% of those with a high school diploma or less. Ph.D. degree-holding entrepreneurs show a monthly disengagement hazard of 53% of those who have a high school diploma or less. Other educational categories were not significant compared to those who have a high school diploma or less.

The only statistically significant comparisons among economic sector categories of the startups are those that aim to operate in the transforming sector. These startups are more likely to disengage compared to those in the business services (base category): their monthly disengagement hazard is +12% of those who plan to operate in the business service sector. Each additional increment in total startup funding (in logs) reduces monthly disengagement hazard by 11%. In addition, for each additional percentage increment in private and external unmonitored funding on total startup funding, disengagement decreases by approximately 1.20%. The only age-range variable that shows significant relationship with time to disengagement was the number of owners age ranged 25-34 (exp coefficient = 1.21, p value< 0.01), meaning that for each additional owner in that age new ventures survive; disengagement hazard decreases by 21% for each additional team member between 25 and 34 years old. The size of the startup team, men, growth preference, degree of innovativeness, and prior start-up attempts did not show any significant statistical relationship with time to disengagement.

Figure 3 shows the Kaplan-Meier estimate for firm creation, illustrating that companies that receive funding twice (blue line) are created faster than those funded once (green line) or never received funding (red line). Approximately 70 months from conception, close to 50% of startups that received external monitored funding at least two times were born. In the case of those that receive external monitored funding one time, it took around 100 months to reach the 50% creation mark. Startups that never received funding required 130 months to reach the same milestone.

However, it is worth noting that confidence intervals overlap each other after month 100, due to the small number of cases that survive until that time.

Figure 3 – Kaplan-Maier estimates for firm creation, stratified by the number of external monitored funding received



Model 2 evaluates the time to the firm creation. At least one of the covariates contributes significantly to the explanation of firm creation. The null hypothesis of the model's overall significance is rejected, and the proportional hazard assumption was met. The model reveals that startups funded at least twice are 54% more likely to become a firm compared to start-ups that never received funding (Table 3). This effect is insignificant when comparing one-time funded startups to those that never received externally monitored funds. Figure 3 illustrates the slight differences between K-M estimates for the never-funded startups (red line) and those funded once (green line), especially during the first 100 months up the gestational phase.

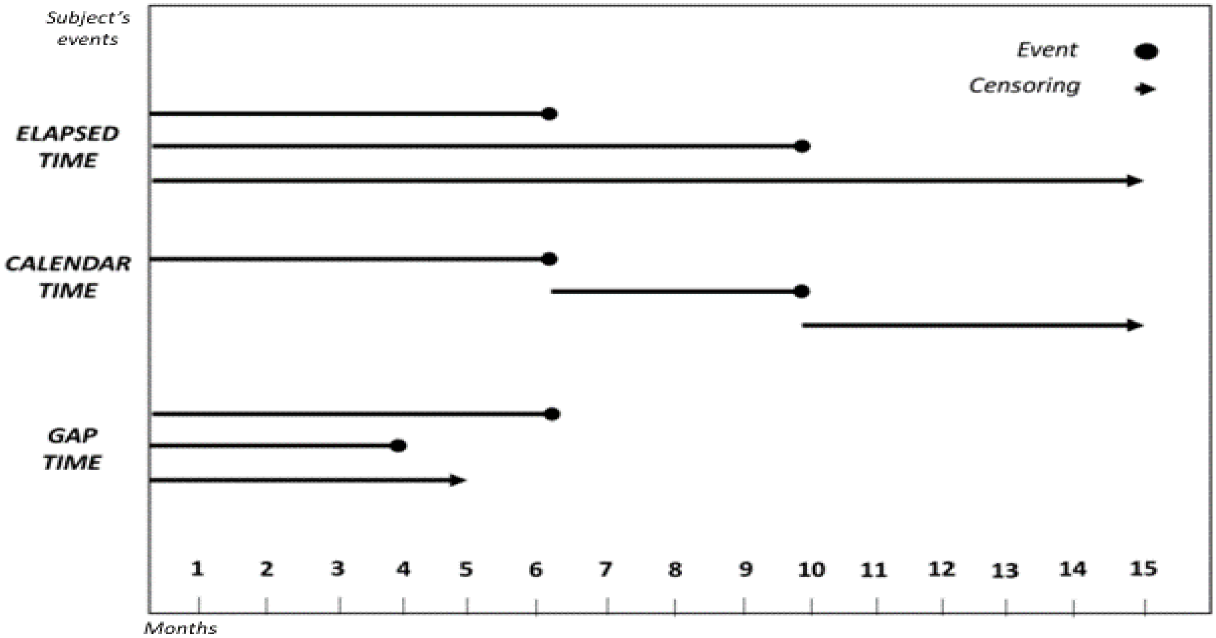
Holding all variables constant, for those entrepreneurs that declared the intention of growing its startup "as large as possible," results reveal a 24% less chance of creating a firm compared to those who declared planning to maintain their company at a "manageable size." The firm creation hazard of entrepreneurs that developed an informal business plan is +38% of those who do not have one, and that number is +35% for whom that developed a formal written plan (but significant at the 10% level). For each additional year of experience of the team in the same economic sector, the hazard of firm creation increases slightly more than 1%. When compared to startups that will operate in the business service sector, the firm creation hazard is +43% of planning to do it in the transforming sector. Finally, each additional increment in total startup funding (in logs) increases monthly firm creation hazard by 5%.

None of the age-range variables show a significant relationship with time to firm creation. None of the following variables are significant in addition: the entrepreneurs' household net-worth, the number of people or institutions that own the start-up, team's sweat equity (total hours), number of white/Caucasians in the team, degree of innovativeness, the financial projections, the prior start-up attempts, the percentage of personal or unmonitored external funding on total startup funding.

4.2 Firm funding

As previously stated, a startup could receive monitored funding many times during its gestational phase. This research accounts for this by analyzing the repeated nature of this event, and the dataset structure also was rearranged for that objective. Figure 4 displays a hypothetical example that describes the possible time-structures for this research. This illustration is the case of a NE who received funding two times in months 6, 10, and his last observation was at month 15.

Figure 4 - Elapsed, calendar, and gap-times structures, hypothetical example



The elapsed time structure will result in observation with events in months 6, 10, and 15 and would have a start and stop times of 0–6, 0–10, and 0–15, respectively. In a calendar time structure, it would result in a start and stop times of 0-6, 6-10, and 10-15, while for the gap time structure these values will be 0–6, 0–4, and 0-5. Gap time is the time-structure that this study uses.

A gap-time data structure was chosen since the underlying hypothesis of this paper argues that there is an effect from receiving external monitored funding for the first time and in subsequent external funding events. Thus, the clock should restart after each event to account for this. Otherwise, if an elapsed-time structure was be selected, the main interest will rely on the effect of covariates on the *kth* event since the time from the beginning of the study and not their effect on the *kth* event since the time from the previous event. Another possibility is the calendar time structure, where the focus is on the effect of covariates on the *kth* event since the time from the previous event, using a fixed starting point (the first observation). The gap time was chosen over this calendar structure since this study does not focus on a specific starting point in time, but it is on the gaps between events.

As explained previously, frailty models are appropriate when there are issues related to heterogeneity. Two Cox regressions with a frailty component (standard and conditional) using a gap-time structure were fitted to explore the factors related to receiving recurrent monitored external funding. Also, Amorim and Cai (2015) and Box-Steffensmeier and De Boef (2006) recommend truncating the database when the number of events becomes small to avoid estimators became unreliable. Thus, the dataset was restricted to 1 (196 cases) and 2 (36 cases) funding events, since there are only ten startups with three and one with four funding events during gestation. The dataset is transformed into a long format where each row contains a startup time with a funding event or censoring time associated, which could be the last time of observation, a firm creation, or quitting from the startup process. As a result, the long format dataset contains 1764 rows, 1532 startups with this censoring time plus 232 funding events. As Allison (2014) pointed out, it is necessary to make all efforts possible to account for right censoring when it is non-random, and that is the case when a startup becomes a profitable new company (firm birth) or when give up the entrepreneurial process. Thus, firm birth and quitting were included as controls aiming to reduce the non-randomness censoring in these models.

Table 4 describes the variables of this dataset aimed to test hypotheses 1, 2, 3a 3b, and 3c. These are the same variables included in Frid, Wyman, Gartner, and Hechavarria (2016) to understand external funding with some additional variables. In these event models, the dependent variable is composed of an event indicator labeled “1” for each repeated event and “0” otherwise. Also, it includes a measure of time in months from the baseline to the first event, between events, or censoring. The event of interest is receiving external funding. As seen in Table 4, on average, the gap times are of 37 months between the events of interest, and 15% of startups obtained external funding.

Table 4 – Descriptive Statistics, Model 3 and 4

	Frailty models	
	Mean	S.D.
Dependent variables		
External monitored funding	0.15	0.44
Time	37.63	29.23
Key Independent variables		
Household net worth, 2005 prices, tertiles	2.01	0.82
Team managerial experience (summation, years)	30.01	29.00
Team industry experience in the start-up economic sector (years)	14.47	16.96
Business plan (base, *no business plan*)	0.55	1.00
Social Capital - Bridging: number of non-owner and non-family helpers	0.96	1.36
dummy, "have developed financial projections" = 1	0.14	0.35
dummy, "Patents, trademarks and copyrights granted" = 1	0.02	0.14
Demographic controls		
Respondent education (base, *high school degree or less*)	1.38	1.03
Number of white/Caucasians in team	1.52	1.40
Number of men in the team	0.95	0.98
Total number of under 24 years old team members	0.13	0.46
Total number of 25-34 years old team members	0.34	0.67
Total number of 35-44 years old team members	0.46	0.70
Total number of 45-54 years old team members	0.44	0.67
Total number of above 54 years old team members	0.41	0.45
Startup characteristics controls		
Legal form of start-up, *base = sole proprietorship*	2.57	1.67
Startup type, *base = independent new venture*	1.48	1.15
Start-up principal economic activity, base = *business services*	1.44	1.33
Entrepreneurs' experience, background and location controls		
Number of team's prior start-up attempts	2.05	4.89
Personal funding / total funding	22.98	37.98
dummy, new venture in metropolitan area = 1	0.74	0.44
Social Capital - Bonding: number of non-owner family helpers	0.54	0.92
Other controls		
Startup creation	0.26	0.44
Startup quitting	0.40	0.49
Conception lag	22.81	22.34

In this section, the key independent variables of interest are those in the hypothesized relationships from H1 to H3b. For example, the mean of the household net-worth (categorical variable) is close to 2 since it is the category of the second tertile[24]. In the case of team managerial experience, it accounts for a mean of 30.01 years since it is the summation of the team's years of

[24] Observations with funding more than one funding events appears more than one time in this dataset (more rows), and for that reason the mean of household net-worth is not exactly 2.

experience. For example, three startup owners with ten years of experience each will result in a value of 30 for this variable. Another key independent variable is the entrepreneurial team's years of industry experience, which shows a mean of 14.4.

Regarding entrepreneurs' networks, on average, each firm has approximately one non-family helper (mean 0.96). Among the signals that entrepreneurs can develop, it is possible to say that most of the entrepreneurs in this dataset do not have a business plan. However, 5% of them have an unwritten plan, 12% have an informal written plan, and 9% have a formal written business plan. About 14% of the cases have completed financial projections, and only 2% have been granted patents, trademarks, or copyrights.

Among the demographic characteristics, again on average, entrepreneurs are mostly educated, are males within 35- and 54 years old, and are from Caucasian ethnicity. Specifically, it is worth noting that most founding teams have at least a college degree since the education mean is 1.38. The average number of males in startups is very close to one (0.95). Thus, most have at least one male on the team, while most start-ups have about one person of Caucasian ethnicity on the team since the average number is 1.52. Regarding age, start-up averages are reported for the five ranges; 35–44 and 45–54 years of age are the most common ranges for start-ups team members.

The 5% of the new ventures operate in extractive sectors, 19% in transforming sectors, and 33% in the consumer-oriented sectors, 42% in the business services sector (base category). The most common startup type are independent new ventures, that account for 82% of cases, while the other categories range from a 7% of sponsored new ventures to a 4% for a takeover new venture. The most common startup legal form is unknown, since when this variable varies it is often not declared (62%) during gestation, while other categories are sole proprietorships (16%), partnerships (6%), limited liability company (3%), C or S-corporations (6%), not yet determined (7%). Lastly, 22.08 is the average time-lag (in months) from conception to PSED initial interview. In terms of location, on average, 74% of entrepreneurial teams operate in metropolitan areas. Also, teams' prior startup attempts average is 2.05, so they are experienced entrepreneurs. The percentage of personal funds on the total startup funding average is 22.98, and only have an average of 0.54 of family members non-owner helpers in the team.

Regarding the model, the first relevant result that emerges from the standard frailty model is the significant within-entrepreneurs correlation seen in the random effect ($\omega = 1.11$, $p<0.001$). In the conditional frailty model (stratified by funding event number), while still significant, the random effect is reduced close to zero ($\omega = 0.17$, $p<0.001$). Hence, this is a signal that factors associated with receiving funding previously made entrepreneurs less heterogeneous.

Table 5 – Standard Frailty and Conditional Frailty Models

	MODEL 3: Standard frailty model, gap-times (event: external funding)			MODEL 4: Conditional frailty model, gap-times (event: external funding)		
	COEF	SE	Exp. coefficient	COEF	SE	Exp. coefficient
Household net worth, 2005 prices, tertiles, base = *beneath the 33rd percentile,*						
between the 33rd and 66th percentile	0.51*	-0.23	1.67*	0.53**	-0.20	1.70**
above the 66th percentile	0.69**	-0.23	1.99**	0.72***	-0.20	2.05***
Team managerial experience (years)	0.03***	-0.01	1.03***	0.02***	-0.01	1.03***
Team industry experience in the start-up economic sector (years)	-0.02	-0.01	0.98	-0.02	-0.01	0.98
Team industry experience in the start-up economic sector (years), squared	0.00	0.00	1.00	0.00	0.00	1.00
Social Capital - Bridging: number of non-owner and non-family helpers	-0.15*	-0.07	0.86*	-0.17**	-0.06	0.84**
Social Capital - Bonding: number of non-owner family helpers	-0.17	-0.1	0.84	-0.1	-0.08	0.90
Business plan (base, *no business plan*)						
unwritten business plan	0.56	-0.32	1.75	0.61*	-0.28	1.84*
informal business plan	0.62*	-0.25	1.86*	0.72**	-0.22	2.05**
formally written business plan	0.3	-0.29	1.35	0.43	-0.24	1.54
dummy, "have developed financial projections" = 1	0.74***	-0.22	2.10***	0.91***	-0.18	2.48***
dummy, "Patents, trademarks and copyrights granted" = 1	-1.09	-0.58	0.34	-0.87	-0.48	0.42
Number of white/Caucasians in team	0.16	-0.14	1.17	0.09	-0.12	1.09
Number of men in team	0.02	-0.09	1.02	0.00	-0.07	1.00
Personal funding / total funding	0.00	0.00	1.00	0.00	0.00	1.00
dummy, new venture in metropolitan area = 1	-0.05	-0.2	0.95	-0.1	-0.17	0.90
Number of team's prior start-up attempts	0.03*	-0.01	1.03*	0.02*	-0.01	1.02*
Respondent education (base, *high school degree or less*)						
tech, community, or some college	0.25	-0.24	1.28	0.13	-0.2	1.14
college or some graduate training	-0.14	-0.27	0.87	-0.07	-0.24	0.93
Master's degree	-0.18	-0.35	0.84	-0.26	-0.3	0.77
PhD degree	0.33	-0.45	1.39	0.35	-0.37	1.42
Legal form of start-up, *base = sole proprietorship*						
partnership	-0.03	-0.33	0.97	0.02	-0.27	1.02
limited liability company	0.16	-0.36	1.17	0.14	-0.29	1.15
C- or S-corporation	-0.06	-0.33	0.94	-0.19	-0.27	0.83
not yet determined	-0.67*	-0.33	0.51*	-0.73*	-0.28	0.48*
unknown	-2.87***	-0.25	0.06***	-2.70***	-0.22	0.07***
Startup type, *base = independent new venture*						
takeover of existing business	1.27***	-0.38	3.56***	0.89**	-0.31	2.44**
franchise	0.87*	-0.42	2.39*	0.78*	-0.36	2.18*
multilevel marketing initiative	-0.2	-0.5	0.82	0.07	-0.43	1.07
startup sponsored by existing business	0.36	-0.35	1.43	0.33	-0.3	1.39
Start-up principal economic activity, base = *business services*						
Extractive sector	1.05**	-0.35	2.86**	0.73*	-0.29	2.08*
Transforming sectors	0.58*	-0.23	1.79*	0.46*	-0.2	1.58*
Consumer oriented sectors	0.45*	-0.21	1.57*	0.43*	-0.18	1.54*
Total number of under 24 years old team members	0.06	-0.24	1.06	0.14	-0.19	1.15
Total number of 25-34 years old team members	0.22	-0.17	1.25	0.27*	-0.14	1.31*
Total number of 35-44 years old team members	0.29	-0.18	1.34	0.35*	-0.14	1.42*
Total number of 45-54 years old team members	-0.17	-0.18	0.84	-0.1	-0.16	0.90
Total number of above 54 years old team members	-0.48*	-0.19	0.62*	-0.43**	-0.17	0.65**
dummy Firm birth = 1	-0.31	-0.24	0.73	-0.11	-0.21	0.90
dummy, new venture quit = 1	0.02	-0.22	1.02	0.12	-0.19	1.13
Conception lag	-0.04***	-0.01	0.96***	-0.03***	0	0.97***
Variance of random effect=	1.190817***			0.1810787***		
R^2	0.37			0.27		

****p < 0.001, **p < 0.01, *p < 0.05*

Hypothesis 1 stated that less-wealthy NEs would be less likely to acquire external funds recursively compared to wealthier NEs. Conditional on the unmeasured heterogeneity, event dependence, and covariates, Model 4 indicates that the odds of a wealthier entrepreneur to get externally funded since the last funding is about 2:1 in comparison to the non-wealthy. When compared to coefficients in Model 3, those in Model 4 with less heterogeneity have more power (significance increased) and are more precise (standard errors decreased).

Hypotheses 2 stated that entrepreneurs with higher levels of social capital are more likely to obtain recurrent external funding. Recall that social capital was measured using different approaches, one related to the entrepreneur's network and another on their status. Model 3 and Model 4 have very similar results. For every one-year increase of NEs' managerial experience, the hazard of obtaining monitored external funds since the last one goes up by an estimated 3%. Industry experience did not account for any statistically significant effect in Model 3 and 4. The effect of non-family external helpers could be surprising: an increase in the number of helpers is associated with a decrease in the hazard of receiving monitored external funds since the last fund by 15% (once more, this effect is stronger in Model 4). This negative relationship should be investigated, but it could be the consequence that helpers are also potential funders for entrepreneurs. Thus, if entrepreneurs have more external non-owner helpers, the need for getting funding might decreases.

The set of hypotheses 3 aim to test the effects of NE's signals, postulating that nascent entrepreneurs that develop business plans, financial projections, or patents are more likely to receive recurrent external funding. Patents, copyrights, and trademarks did not show significant results in Models 3 and 4, but it is worth recalling that very few (2%) entrepreneurs during the gestational phase have granted a patent, copyright, or trademark (Table 4). However, unsurprisingly, developing financial projections is the signal that accounts for the highest "hazard" in reducing gap times for receiving external monitored funding: the odds of being funded since the last external monitored funding event are 2.5 to 1 for those NEs that develop financial projections compared to those that did not. This effect is more precise in Model 4 than in Model 3, since standard errors are smaller in the former. In Model 4, business plan accounts for an interesting effect: The odds of NEs with an unwritten business plan receiving external funding since the last funding event is about 1.8:1 in comparison to those that did not develop any business plan. Compared to NE's without any business plan, the odds of receiving external funding for NEs with a non-formal written plan are 2:1. However, the hazard of getting funded for those that have a formal written business plan shows the expected sign, but only at a 10% level. Model 3 shows similar coefficients, but with higher standard errors and less power.

Regarding the control variables, an additional prior start-up attempt increases the hazard of receiving external funds recurrently by 3% and 2% in Model 3 and 4, respectively. Compared to sole proprietorships, other legal forms show a reduced hazard of receiving externally monitored funding since the last event. For example, "not yet determined" and "unknown" account for 48% and 7% of the sole proprietorship's hazards of receiving recurrent monitored external funding. Looking at the type of startup, the odds for receiving external monitored funding of takeover new ventures are almost 2.5:1 of those independent new ventures. In the case of franchises, their odds are 2.1:1 compared to independent new ventures. The odds of receiving *kth* funding since the previous one for those startups aiming to operate in extractive sectors are 2:1 of those in the business services sector. Startups intending to operate in transforming sectors and consumer-oriented sectors account for 58% and 54% of the hazard of receiving external funding since the previous funding event compared to business services (Model 4) Always, Model 4 accounts for more precise and robust estimators.

In Model 4, an additional owner aged between 25-34 and 35-44 reduces the time-gap to receiving external monitored funding since the last event. For every extra member among 25-34, the hazard of receiving external monitored funding after the previous one goes up by 31%, and 41% in the case of owners aged 35-44. Contrarily, each additional owner of 54 years old or older, reduces the hazard of recurrent financing by 35%. This owner age range is the only significant variable in Model 3 among age-range variables. The number of non-owner family helpers, white/Caucasians, and the number of men in the entrepreneurial team were not of statistical significance in Model 3 or 4. Also, the percentage of personal funding in the startup total did not show any significant relationship with reducing the gap to receipt external funding. Neither did the following variables: the entrepreneur's household net-worth, the rural/urban location of the startup project, nor the respondent's educational level.

4.3. Summary of the main results

This paper provides evidence of the effects of receiving external monitored funding more than one time on firm survival and creation. Recurrent funding increases both the survival of new ventures and accelerates their creation significantly, with the relationship becomes statistically stronger in the case of survival. The Kaplan-Meier estimates show the effect of receiving monitored funding at least twice has on firm survival, with almost 90% of firms funded at least twice surviving during the observation period.

For this reason, this study also offers evidence about who receives external monitored funding recurrently. H1 hypothesizes those NEs coming from a more affluent background obtain external monitored funding recurrently sooner. The findings provide convincing evidence that those entrepreneurs have shorter time gaps between each external funding event than less affluent counterparts. H2 hypothesizes that social capital reduces gap times between finding events, and the status-associated dimension of social capital, measured by teams' years of managerial experience, confirmed this relationship. However, teams' years of industry experience is not statistically associated with reducing gap-times in receiving external monitored funding. Social capital measured using entrepreneur's networks shows the opposite direction expected. We suggested an explanation for this unexpected relationship that requires additional investigation. The number of helpers who can potentially aid entrepreneurs in obtaining funding may explain this outcome, an area requiring further investigation.

In addition, this study found evidence that developing signals can reduce gap times in receiving external monitored funding, as the third set of hypotheses suggested. However, some signals are more powerful than others. For example, patents were not significant in reducing monitored funding gap times, but it is worth remembering that only a few NE's have one granted during gestation. NEs who developed financial projections reduced gap times in receiving external monitored funding, while the development of business plans did as well. Both unwritten and informally written business plan are significant in reducing monitored funding gap times compared to not having one, although the comparison between having a formal written business plan and not having one is significant only at the 10% level.

5. DISCUSSION

This study provides evidence that receiving external financing during the entrepreneurial process is a dynamic process influenced by social factors. Receiving external monitored funding several times during the gestational phase enhances firm survival and creation. Also, those who are more likely to receive funding several times during the gestational period are NEs coming from a wealthy background and high social status. This study provides initial evidence of a potential

Mathew effect in entrepreneurship financing. However, other factors related to entrepreneurs' actions in developing signals for investors and lenders are on influence and might reduce this effect.

This study extends on Hechavarría *et al*. (2016), a research that examined how the capital structure of startups impacts on their survival and creation. In our study, the dynamic nature of funding through the gestational phase revealed the importance of receiving external monitored funding several times as a critical determinant for a firm's survival and creation. Although there are some divergences in results regarding the control variables, most of the outcomes of this research agree with Hechavarría *et al*. (2016). For example, they found that firms primarily financed with external equity show a 47 % increase in the incidence of new firm founding over time (Hechavarría *et al*. , 2016). In our models, these variables were not of interest. However, this study found that receiving external monitored funding several times, which might increase the external equity in a startup's capital structure, supports Hechavarría *et al*. (2016). Additionally, they found that there is a significant decrease in the incidence of disengagement over time for startups financed primarily with debt and external equity. In this research, Model 1 revealed that receiving external monitored funding at least once during the gestation significantly decreases the risk of disengagement, as well.

Using a different modeling strategy and only data from PSED II, Frid, Wyman, and Coffey (2016) found that compared to wealthier entrepreneurs, those coming from a low-wealth background are less likely to acquire external financing. This study found evidence that supports their conclusion that wealthier entrepreneurs are more likely to receive external monitored funding several times. Previous research has found that social origin influences the reception of external funding (Frid, Wyman, Gartner, and Hechevarría, 2016; Frid, 2014). This study showed that economic and social origin influence the reception of external funding several times during entrepreneurial gestation.

However, the models developed in this research analyzed the repetitive nature of the funding event, suggesting some differences with previous investigations. While race has been mentioned as a critical factor in explaining receiving monitored funding (Frid, Wyman, Gartner, and Hechavarría, 2016; Frid, 2014; Gartner *et al*., 2012), this research found that race is not a critical factor associated with recurrent external monitored funding. In Frid Wyman, Gartner, and Hechavarría's (2016) models, African-American entrepreneurs are less likely to acquire external funds than Caucasians. However, this relationship was found to be weak statistically, supporting Casey's (2014) findings regarding the external financial amount that non-Caucasians receive. Unlike these studies, our research measured race counting the number of White/Caucasian owners during the gestational phase, and did not find any significant association with the repeated event of monitored funding. In various other research fields, there are many examples where race effects disappear after including socioeconomic variables, and entrepreneurship research does not an exception. In this regard, another possibility to for future research is that race could be an inhibitor for minority-owned startups to get their first external funding, but, once funded for their first time, the effect of race as an inhibitor might disappear for further funding events.

The findings from this research also highlight that both business planning and preparing financial projections are associated with receiving external monitored funding. Thus, the entrepreneur's ability to develop signals might affect receiving external monitored funding recurrently and thus, accelerate firm creation and deaccelerate disengagement. It is possible to assert that preparing financial or business plans for potential investors likely diminishes the information asymmetry between lenders and borrowers and subsequently reduces transaction costs for both parties. Therefore, the Mathew effect of the wealthier and well-connected entrepreneur is likely to be reduced if those coming from less privileged backgrounds are more exposed to these activities. These findings suggest that hands-on financial practice is associated with an increase in the likelihood of receiving funding recurrently. The heterogeneity reduction found when the model was stratified by a funding event (Model 4) indicates something a similar pattern. There is probably a learning process for entrepreneurs for getting funding for the first time, but this cannot be confirmed, only suspected, based on the models of this research since it was not directly tested. It is also possible that banks, institutions, and any lender in general, can ask for a business plan after identifying a viable project. A specific study designed to detect causality could shed light on this regard.

Other variables were not of significance in explaining getting funding more than once, and some of them can be even considered a contradiction to what has been found previously. For example, NEs that invested more personal funds, as a proportion of the total startup funding, are less likely to get funded recurrently as previous studies suggested (Frid, Wyman, Gartner, and Hechavarría, 2014; Frid 2014). Contrary to what has been found in Frid, Wyman, Gartner, and Hechavarría. (2016), entrepreneurs' private funding investments do not act as a signal for external borrowers who monitor their money or loans when all funding events during gestation are considered. These differences should be further investigated. However, one possible suggestion is that the "skin in the game" hypothesis is plausible just for the first funding received. After being funded for the first time, and therefore, after "signaled" the project as viable for external funders by obtaining an external fund previously, there may not be a relationship between the personal funds invested in obtaining further external financing.

6. IMPLICATIONS

Time is central to the understanding of entrepreneurship ((Bird & Page West III, 1998), pg. 6) argue that *“temporal issues uniquely and explicitly characterize the entrepreneurial process”*; yet, temporal issues are some of the most challenging to comprehend. Time is a valuable, if scarce, resource, and one goal of this research was to understand whether receiving external funding several times during gestation has implications for accelerating firm creation or attenuating their disengagement from the entrepreneurial process. Being funded repeatedly was demonstrated to be a crucial resource for entrepreneurs to operate and survive the nascent stage of the startup process.

In this study, data from the PSED I and II were used to provide new evidence on entrepreneurs’ characteristics associated with the reception of external funding. Overall, the findings challenge the assumed benefits associated with pecking order theory, where entrepreneurs first use their funds and then attempt to obtain external funding. When the repetitive nature of external monitored funding is taken into account by letting the hazard vary by event number and accounting for individual heterogeneity, the personal funds invested in the startup are not of significance in receiving external funding recurrently during gestation. However, signals that reduce asymmetrical information for investors and lenders do affect the hazard of receiving external monitored funding recurrently, as does as entrepreneurs’ social background.

This study has three main implications. First, it adds another piece to the growing literature analyzing data from the PSED project by presenting new evidence on the benefits of external funding for entrepreneurs. Specifically, this study considers the repeated nature of receiving external monitored funding. When time is considered, the time-varying nature of the variables must be considered as well, leading to outcomes that differ from previous research findings. Therefore, the need to account for time is emphasized when analyzing entrepreneurial funding.

Second, this research indicates that the number and the timing of the external monitored funding received by entrepreneurs impacts on firm survival and creation. Among startups that received funding several times, virtually all survived, and a high percentage become profitable firms. The startups that obtained external monitored funding only once survive longer than those that never received funding, but only during the first years of gestation. It seems that the impact of receiving external monitored funding decreases with time, and if the venture does not receive further funding, its positive effects on survival disappear.

Third, this research also suggests that some characteristics pointed out by the Matthew effect theory might operate in the entrepreneurial reward system. This study confirms that wealth and managerial experience are positively associated with receiving funding in shorter periods. Contrary to what can be inferred from previous studies, the personal funds invested do not seem to affect the reception of external monitored funding when the repetitive nature of this event is considered. The same applies to race, measured as the increasing presence of white owners in startups. Further investigations are needed to understand if these factors only affect the first funding received. However, factors such as socio-economic background (wealth and status) appear to be the critical factors for obtaining of getting external monitored funding as well as business plans and financial projections.

Fourth, as mentioned previously, signals for investors and lenders, such as business plans or financial projections, positively affects the likelihood of receiving funding more than once during the gestational phase. These factors are not necessarily related to entrepreneurs' social or economic origin. Thus, there is room for targeted policy approaches that could provide opportunities to groups of potential entrepreneurs from underserved groups. Entrepreneurial education programs, hands-on internships, or mentoring can help these entrepreneurs in developing skills to formulate business plans and financial projections for their entrepreneurial projects. Future research evaluating the success of these types of programs and their costs and benefit would add value to our understanding of this process.

7. LIMITATIONS AND FUTURE RESEARCH

In this study, startups were not analyzed after gestation, and important limitation because profitable firms (based PSED definition, when firms born) could be more likely to attract investors and receive more external funding after gestation. In this research, the focus was on one phase of the entrepreneurial process. Future research can extend upon this study by more thoroughly exploring the start-up process during the nascent stage (after profitability).

This study also highlighted the importance of receiving external funding more than once during the gestational phase and the factors associated with it. However, there is a blind spot about performance outcomes other than startup creation and survival that could mediate the effect of receiving external funding. For example, are those startups that receive external funding repeatedly more likely to transition from a sole proprietorship to hiring its first employee? Have these startups increased their earnings after receiving external financing? Further research combining new venture's performance outcomes and the reception of funding could shed light on these questions.

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CHAPTER FOUR

CREATIVE-ENTREPRENEURS AND NEW VENTURE PERFORMANCE: A STUDY OF THE CREATIVE CLASS AT THE FIRM-LEVEL

1. INTRODUCTION

Creative Class Theory (CCT) proposed by Richard Florida in his book *The Rise of the Creative Class* (2002) had a vast influence on regional studies and economic geography. Today, when talented individuals' mobility is thought to be increasing, CCT describes what factors lead these skilled people to settle in specific regions and not in others, and more importantly, their impact on regional economic development.

Since the release of Florida's book, CCT and its relation to entrepreneurship and innovation have been extensively applied to most of the high-income countries of the world. The conceptual framework of the creative class has been extended and criticized in the academy, while at the same time, it has been understood by policy-makers as a critical guide for today's urban and regional growth. There is significant evidence supporting CCT's central thesis, which states that there is a relationship between the percentage of creative workers and economic development in a region, specifically regarding entrepreneurship and innovation for U.S., Canadian, and European metropolitan areas. CCT suggests an alternative way of measuring human capital. Based on an individual's occupation, it specifies a set of professions that make up the "creative class," which includes scientists, artists, entertainers, and a wide range of knowledge-based professions across "classic" activities such as management, finance, law, healthcare, and education.

Instead of focusing on the regional level, this paper investigates the influence of creative individuals at the startup level. The creative class has been found to impact regional levels of entrepreneurship, but this alternative way of approaching human capital has been overlooked at the firm level. Given the significant evidence of the relationship between the creative class and regional entrepreneurship, this study focuses on new venture projects and their entrepreneurial teams by investigating the following question: Does a higher number of creative individuals on entrepreneurial teams improve startup performance?

2. THE CREATIVE CLASS THEORY AND ENTREPRENEURSHIP

2.1 - The creative class theory

According to The Creative Class Theory (CCT), the availability and quality of people shape differences in regional economic performance; thus, it is possible to classify CCT among human capital theories. The conventional approach to human capital is based on educational attainment, usually measured by an individuals' years of formal education or other indicators such as having or lacking a bachelor's degree or postgraduate studies. CCT relies on a different approach, measuring people's activities on their work instead of what they have studied. The critical difference between this occupation-based approach and the classical human capital approach is its focus on individuals' daily activities instead of the educational level or the economic sector in which people work since people do not necessarily receive formal schooling for the jobs they perform. For example, one person without formal information technologies (IT) degree can perform IT tasks in his or her job for a company not related to the IT industry. The educational background and economic sector do not entirely reveal what people do on their jobs.

Florida (2002, 2012) theorized that there is a social group, the creative class, with a shared core of norms and values that identify problems and new solutions by creating new knowledge. The creative workers are valued primarily for their mental work. CCT differentiates creative workers to those who are paid mainly for performing physical tasks, namely the working class, or for their physical presence, which is the service class.

The creative class also has an internal composition. Florida established a hierarchy of different creative individuals, the super-creative core, the creative professionals, and the bohemians. The super-creative core consists of those specialists who focus primarily on research activities, finding and anticipating new problems to solve. These individuals have a high degree of formal education and often received a college degree, at least. Engineers, mathematicians, doctors, physicists, chemists, economists, and astronomers, among others, characterize this subgroup. A second creative class sub-group is the “creative professionals,” who work primarily on creative problem-solving. The creative professionals regularly perform tasks that require thinking on their own and applying and combining standard approaches to fit different situations. They use their great deal of judgment to create radically new solutions in their work, for example, various management occupations. Lastly, the third sub-group is the bohemians, defined as those who spend a significant proportion of their working time performing artistic tasks, such as designers or musicians[25].

CCT outperforms conventional human capital measurements based on individuals’ educational levels in accounting for regional development. For example, Florida, Mellander, and Stolarick (2008) found that while the classical approach to human capital impact positively product and wealth, the creative class-related variables have been found to have a stronger impact on employment and wage growth. Similarly, Qian (2017a) estimated spatial regressions to analyze regional entrepreneurship levels, finding that labor skills, rather than education, are positively related to high-tech entrepreneurship in the US metropolitan regions. In a second study, Qian (2017b) examined Florida’s hypothesis with the goal of enhancing his precision; to do so, he

[25] The codes used for creating the creative class occupations, variables, and modeling can be provided by contacting the author.

investigated the relationship between skill categories and entrepreneurship, finding that problem-solving skills, like the ones proposed in CCT, revealed both a direct and moderating effect on high-technology entrepreneurship regionally.

In summary, the central thesis of CCT hypothesizes a positive relationship between the presence of these creative workers and regional economic development (Florida, 2002). A higher percentage of creative workers in a region fosters higher rates of new firm formation and employment creation. CCT has been applied to several regions of North-America (Florida, 2012, Kundsen, Florida, Gates, and Stolarick, 2008; Florida, Mellander and Stolarick, 2006; Lee, Florida, and Acs, 2004), and Europe (Andersen, Hansen, Isaksen, and Raunio, 2010; Boschma and Fritsch, 2009; Marlet and Van Woerkens, 2004).

2.2 The creatives at the firm level

Past research has been found that human capital dimensions influence new ventures through different mechanisms. Supply and demand factors related to human capital can foster regional entrepreneurship. From the supply side, the entrepreneur's educational level positively influences new venture productivity (Fairlie and Robb, 2007; Smith, Collins, and Clark, 2005; Davidsson and Honig, 2003) as well as a more educated labor force (Subramaniam and Youndt, 2005). From the demand side, the level of education shapes consumption (Witt, 2001) and fosters the creation of innovative startups. The demand for more innovative products increases in regions where the human capital level of the population is high (Buenstorf, 2003).

The classical approach to human capital using education-related variables has been widely applied in understanding new venture performance. However, the creative class approach, which questions the classical human capital approach at the regional level, has not been investigated at the firm level. Thus, this paper explores the latter, specifically focusing on the supply side by examining how the number of creative entrepreneurs on startup teams affects new venture performance. The underlying hypothesis of this study is a superior startup performance among entrepreneurial teams increases as the number of individuals with a creative background increases. Although a positive association between a higher creative class presence has been found with regional entrepreneurial rates, it has not been investigated if the creative class affects the supply side, the demand side, or both. This paper aims to investigate the supply side, specifically focusing on entrepreneurial teams aiming to create a new company and evaluating how creative members foster or inhibit their new venture performance.

One limitation of regional entrepreneurial studies is the dependent variable used. Often, the outcomes evaluated in regional studies a firms' births or death rates. These indicators are biased outcomes of the entrepreneurial process, as evaluating firm births ignores a significant number of projects that are still trying in the creation process at the moment of counting new births (primarily new registered companies). Thus, using firm births as the dependent variable biases the analysis of the entrepreneurial process towards the most successful companies. In addition, analyzing failure via firm deaths also biases the results; as an example, it only counts already registered companies that stop their operations. There is a significant number of startup projects that fail before than registration occurs. By analyzing only these outcomes, it is not possible to know how the higher availability of creative individuals affects regional entrepreneurship. One possibility is that having more creatives in a region might push the demand for more innovative and niche products provided by local new ventures. Another possibility is that entrepreneurs coming from creative occupations, namely in this research the creative-entrepreneur, perhaps can initiate better entrepreneurial projects, or could hire more such employees. Investigating the last requires research at the firm level. The objective of this research is to examine the relationship between creative-entrepreneurs and their performance at the startup microlevel.

Specifically, the goal is to estimate the contribution of an additional creative-entrepreneur in the startup team to several measurements of startup performance. The first performance outcome investigated is the survival of the new venture, aiming to test the persistence of entrepreneurial projects led by creative-entrepreneurs. Secondly, the transition from own-account to employ the first worker is evaluated. Then, the analysis focuses on the total number of employees hired by the new venture. These two indicators aim to examine if entrepreneurial projects led by more creative entrepreneurs generate a higher level of employment. Finally, the focus moves to startups' earnings, seeking to verify if entrepreneurial projects run by creatives-entrepreneurs are feasible in terms of profitability. The last outcome evaluated is the time to reach the sixth month of earnings in a row.

2. 2. 1 Firm survival

As pointed out previously, creatives individuals specialize in innovative tasks and products. Therefore, they can create niche markets or entirely new markets where competition is virtually nonexistent. Companies led by creative-entrepreneurs might seek to operate in those markets, and as a consequence, increase the survival chances of their new ventures precisely because of the limited competition they face (Kim and Mauborgne, 2014). Also, innovative entrepreneurs present higher survival chances of their startups since the demand for new products and services increases as consumer's wealth increases (Jackson, 1984). It also has been found that innovative firms tend to survive for a longer time (Cefis and Marsili, 2005) to less innovative ones, and as mentioned, the creatives are positively associated with more innovative places (Whitacre, Meadowcroft, and Gallardo, 2019; Knudsen, Florida, Gates, and Stolarick, 2008). Therefore, hypothetically, entrepreneurial teams in which there is a higher presence of creative-entrepreneurs are more likely to maintain their companies operatives for a more extended period; formally, it is hypothesized that:

H1: *Having more creative entrepreneurs on entrepreneurial teams extends a firm survival*

2. 2. 2 Job creation

As mentioned previously, creatives individuals are innovative and have a special ability to solve problems. There is an ongoing debate about the role of innovation as a factor for job creation or the loss of existing jobs (Ciriaci, Moncada-Paternò-Castello, and Voigt, 2016; Mansury and Love, 2008; Greenan and Guellec, 2000). However, it has been found that young firms drive job creation (Haltiwanger, Jarmin, and Miranda, 2013; Haltiwanger, Hyatt, Mcentarfer, and Sousa, 2012), and additionally, there is evidence that a higher percentage of creative individuals is associated with higher levels of job creation regionally (Boschma and Fritsch, 2009), especially high-tech jobs (Andersen, *et al.* 2010). Thus, it is possible to formulate the second set of hypotheses for this study, suggesting that more creative-based entrepreneurial teams will create more jobs and more quickly. Formally:

H2a: *The higher the number of creatives on entrepreneurial teams, the faster the transition from own account projects to hire the first employee.*

H2b: *The more creatives on entrepreneurial teams, the more employees hired.*

2. 2. 3 Profitability of new ventures

Florida *et al*. (2008) found that classical human capital is more strongly associated with the GDP than to creative occupations. Thus, following the logic of applying regional-level findings to firm-level findings, one could expect no association between creative-entrepreneurs and profitability. However, since creative individuals are innovation agents and thereby associated with the creation of niche markets or new markets, creative entrepreneurs could earn higher profits by creating pioneering new ventures that face low competition (Kim and Mauborgne, 2014). Thus, it is hypothesized that:

H3: *The higher the number of creative in entrepreneurial teams, the faster the firm will reach the profitability status of their new ventures.*

3. METHODS

3.1 Scope and unit of analysis

The relationship between creative class and entrepreneurship has been investigated primarily by regional and urban scholars. As Perry reviewed (2011), CCT provides three primary types of evidence regarding its connection to economic development, at times using entrepreneurship-related variables as proxies. The most important approach explores situations where regionally the creative class is higher, using statistical methods to verify hypothetical relationships to determine superior business performance. The second approach tries to explain why there is a relationship between CCT and entrepreneurship, primarily mostly on case studies and qualitative methods, gathering primary information on individual participants in various urban settings. The third approach examines the regional context by focusing on policies, local features. While the first approach prevailed among CCT scholars, it has rarely informed about causal relationships. In these approaches analyzed by Perry, the unit of analysis was a region, such as a country, a state, or a metropolitan area. In contrast, the unit of analysis of this study is the entrepreneurial team, delimiting the scope of this investigation to the firm level instead of the regional level to analyze the impact of creative-entrepreneurs on startup performance, during the gestational phase.

The PSED project defines startup gestation as the moment of startup conception. This event occurs when an entrepreneurial team first reports having done a pair of "start-up activities" within 12 months[26]. The earliest date of this first pair is considered the conception day of the start-up process (Reynolds, 2017). The startup gestation lasts until the nascent entrepreneur(s) achieve six months of profitability; this event is considered to be the birth of the new company. Thus, startup gestation extends until the new company is launched. However, during gestation, nascent entrepreneurs can disengage from the gestational phase before launching. By observing the gestational phase, it is possible to investigate the actual transition from not having a business to operating one in the US economy as well as other factors associated with this phenomenon.

3.2 Dataset and samples

Three datasets were combined for this research: The PSED I, the PSED II, and the PSED harmonized transition outcomes dataset. PSED-I and PSED-II offer representative and publicly available[27] samples of individuals attempting to start a company at the U.S. scale focused on the business formation process. It is one of the few studies that provide data on new venture founders about the timing to create a new firm or to disengage from the start-up process (Gartner and Shaver, 2012). To be considered a nascent entrepreneur during the screening process, the respondent had to answer positively that they *‘‘(a) considered themselves in the firm creation process; (b) had been engaged in some behavior to implement a new firm—such as having sought a bank loan,*

[26] As mentioned in the previous chapter, these startup activities are: Invested own money; Began business plan Developed model, prototype; Purchased materials, supplies, parts; Define markets to enter; Promote products or services; Sales, income, or revenue; Leased, acquired major assets; Talk to customers; Financial projections; Full time start-up work; Saving money to invest in firm; Phone book listing for business; Established bank account for firm; Obtained supplier credit; Began to organize start-up team; First use of physical space; Hire lawyer; Business plan finished; Model, prototype fully developed; Signed ownership agreement; Proprietary technology developed; Invested own money; Investment in legal business; Know listed in Dun and Bradstreet; Signed ownership agreement; Full-time start-up work; Invested own money; Received patent, copyright, trademark; Signed ownership agreement; Signed ownership agreement; Invested own money; Full time start-up work; Signed ownership agreement; Invested own money; Full time start-up work; Full time start-up work. Serious thought on starting a company it is an activity asked, but it is not considered to start or end counting gestations since virtually all entrepreneurs mentioned it (see Reynolds, 2017)

[27] Access for PSED-I, PSED-II and the consolidated data set can be found at www.psed.isr.umich.edu

prepared a business plan, looked for a business location, or taken other similar actions; (c) expected to own part of the new venture; and (d) the new venture had not yet become an operating business" (Reynolds and Curtin, 2008:172). Based on these screening questions, PSED-I and PSED-II ended up with 830 and 1214 respondents, respectively. PSED-I has a maximum of four waves for collected between 1999 and 2003, while PSED-II consists of a maximum of six waves, collected between 2005 and 2012.

Combining PSED-I and II resulted in 2044 cases, but only 1599 respondents are considered for analysis. These respondents are considered the "good cases" from PSED because these individuals are active nascent entrepreneurs interviewed at least twice (one or more follow-up interviews) in the PSED harmonized transitions dataset (Reynolds and Curtin, 2011). The final sample size for each model developed here differs. The number of cases under analysis in Models I to III (Hypothesis 1) is 1544, as a result of dropping 14 cases because their conception dates were defined after the first interview. These are problematic to this research because, by including these cases, it adds another period of observation before the conception date. In addition, 41 cases were removed due to the lack of information about household net-worth, one of the control variables described below. In the case of Models IV-IX, 25 cases were also dropped due to extreme outliers detected in the dependent and control variables[28]. As a result, when evaluating Hypotheses 2a and 2b, the number of cases is 1519. Finally, when evaluating profitability, the subsample represents those entrepreneurial teams who have not disengaged but have remained in gestation or created a new venture. Therefore, when evaluating Models X, XI, and XII, the number of cases is 901. All models are weighted to align the PSED II sample to the U.S. Department of the Census

[28] This study followed a conservative strategy of removing outliers by eliminating those cases exhibiting a standard deviation higher than |6| in any of the variables included in the model, resulting in dropping 25 cases.

Current Population Survey using the weights provided in the PSED harmonized transition dataset, ensuring the generalizability of the findings to the population of nascent entrepreneurs in the USA.

3.3 Methodological strategy

The sample from the PSED project is representative of the number of U.S. individuals of individuals attempting to start ventures between 2000 and 2012. At some point during this gestation period, every respondent in the sample has started a new venture, has disengaged from the process, or is still trying to start a business through the end of the observational period. Four outcome variables are used here to evaluate the contribution of an additional creative entrepreneur on startup performance, and the modeling strategy varies depending on the outcome variable evaluated.

Various control variables that previous research found to influence the entrepreneurial process were also included, as they are likely to influence the startup outcomes. More specifically, the control variables included are similar to the ones in the models of Hechavarría, Matthews, and Reynolds (2016), who evaluated new venture survival combining PSED-I and II. When the times of the first employee hired, the number of employees, and the profitability for six consecutive months are evaluated, the variables used by Frid, Wyman, and Coffey (2016) are applied. The outcomes from Frid, Wyman, and Coffey (2016) are comparable to the ones in this study, except that they used PSED II only and not PSED I and II combined, as in this study. Frid, Wyman, and Coffey (2016) used the total revenue as a dependent variable, and instead of that variable, six months consecutive of profits is evaluated in this study. It is not possible to use revenues when combining PSED-I and II since both projects measure different outcomes: in PSED-I, asked for expected revenues instead of the actual revenues, are asked in PSED-II.

Therefore, six consecutive months of profitability, or under the PSED approach, refers to firm births, is used as an outcome variable of profitability here.

3.4 Dependent variables

The primary interest of this study is to explain variations in the business performance of entrepreneurial teams. The first outcome analyzed is a performance measure of survival of the entrepreneur's start-up using the variable QUIT to detect whether entrepreneurial projects have disengaged or not. QUIT is coded as "1'" for entrepreneurial teams or solo projects who disengaged during startup gestation and "0" for those remained in gestation and or started a new firm. This study is interested in those cases that did not disengage from the entrepreneurial process, the cases coded "0." The PSED project defines disengagement differently for PSED-I and II. In the former dataset, it is coded "1" if the respondents claim they have terminated work on the start-up, while in the latter they claim little recent work on the start-up, no future work on it, and that future career plans do not include any new effort on this start-up (Reynolds and Curtin, 2011).

Secondly, as a proxy for how fast a startup project creates jobs, this study analyses the time taken to hire the first employee. These startups include those that have disengaged from the entrepreneurial process, or still trying to become profitable firms, or are already profitable. The time in months from the conception of entrepreneurial projects to the first employee hired is the time used, and it is labeled "1" in the variable FEMP and as "0" for those startups that never hired an employee. These last cases are treated as right-censored if they are interviewed in the last PSED wave and have not hired their first employee yet.

The third outcome variable evaluated also aims to analyze the entrepreneurial teams' capacity to create jobs. EMPlog, which is the number of employees hired (in logs) for each wave in the panel dataset, is a left-censored variable since many entrepreneurial projects never hired an employee or did not hire one within the PSED's observation period. This situation inflates the number of zero cases in this variable, and the remaining part of the curve shows a close to normal distribution. Section 3.6A discusses the special treatment of this variable.

The fourth outcome variable aims to measure the ability of entrepreneurial teams to design profitable ventures, and it is analyzed using dummy variable PRF6. If the revenues of the new venture cover all expenses, including owners' wages and salaries during the last six of the past twelve months, this variable is coded "1" and "0" if otherwise. The time in months from the conception of the entrepreneurial projects to the date of six consecutive months of profits reported is the time of the event "becoming a profitable new firm."

3.5 Independent variable

The primary independent variable is the number of creative entrepreneurs on the entrepreneurial teams. Creatives, as mentioned previously, are individuals who make their living based on their inventiveness and originality. For each entrepreneurial team and each PSED wave, this treatment variable measures the number of startup owners that held a creative job before initiating the current startup project. The occupational codes used to compute the creative jobs are the same provided by the USDA's Economic Research Service (ERS) using Standard Occupation Code (SOC), which is available in the PSED datasets, and available in Table 1.

Table 1 – Occupation of the Creative Class, SOC code

	Standard Occupation Code (SOC)
Management occupations	
Top executives	11-1000
Advertising, marketing, promotions, public relations, and sales managers	11-2000
Financial managers	11-3030
Operations specialties managers, except financial managers	11-3010, 11-3020, 11-3040 through 11-3070
Other management occupations, except farmers and farm managers	11-9020 through 11-9190
Business and financial operations occupations	
Accountants and auditors	13-2011
Computer and mathematical occupations	
Computer specialists	15-1000
Mathematical science occupations	15-2000
Architecture and engineering occupations	
Architects, surveyors, and cartographers	17-1000
Engineers	17-2000
Drafters, engineering, and mapping technicians	17-3000
Life, physical, and social science occupations	
Life and physical scientists	19-1000 and 19-2000
Social scientists and related workers	19-3000
Legal occupations	
Lawyers	23-1011
Education, training, and library occupations	
Postsecondary teachers	25-1000
Librarians, curators, and archivists	25-4000
Arts, design, entertainment, sports, and media occupations	
Art and design workers*	27-1000*
Entertainers and performers, sports, and related workers*	27-2000*
Media and communications workers	27-3000 and 27-4000
Sales and related occupations	
Sales representatives, services, wholesale and manufacturing	41-3000 and 41-4000
Other sales and related occupations, including supervisors	41-1000 and 41-9000

**These two categories comprise the arts occupation subset.*

Source: USDA, Research Division: available at www.ers.usda.gov/data-products/creative-class-county-codes/documentation

In both PSED I and II, respondents were asked to disclose their and their teammates' (if any) previous job. In addition, if new team members join the venture during the period of observation, respondents must report their previous jobs as well. Therefore, the variable CCE is a time-varying variable that measures the number of creative entrepreneurs observed for each entrepreneurial team (j) in each PSED wave (t). The PSED variables that report the previous job of the entrepreneur are T(1-5)OCC, R, S, and T-686_1-6, for PSED I, and for PSED II the variables used are A, B, and C-H1_6, and D, E, F-H1_10. Further, another variable that accounts for the percentage of creatives among entrepreneurial teams is tested. This variable is calculated using the CCE divided by the number of startup owners (TEAM), resulting in the variable CC% = (CCE/TEAM*100).

3.6 Additional control variables

The variables used in this paper are similar to those used in Hechaverría *et al*. (2016) and Frid, Wyman, and Coffey (2016). In their study, Hechavarría *et al*. (2016) investigated the effect of funding sources (equity and debt) on firm survival and creation. Because under the PSED approach, the firm creation happens when the revenue received in 6 of the past 12 months covers all expenses, including owners' wages and salaries. Thus it is directly linked to the new venture's profitability. Since Hechaverría *et al*. (2016) merge both PSED I and II as is done in this study, the control variables used here are very similar to theirs. However, in the case of the employment models, the research reported here is unique in evaluating this dimension using both PSED datasets. After exploring earlier articles on the topic, Frid, Wyman, and Coffey (2016) analyzed the number of employees hired during the first year of the startup's operations using only PSED II. In this study, extends Frid, Wyman, and Coffey's (2016) models using both PSED I and II[29].

[29] Some of the control variables used by Frid *et al*. (2016) are impossible to be included in the models of this study. For example, that is the case of "gainfully employed at the decision to start" because is only available for PSED II as well as "community support". Also, this study does not explicitly control for "time in gestation" as Frid *et al*. (2016) did, since our modeling strategy considers time as an intrinsic part of it (survival analysis and Tobit random effect models using panel data).

3.6.1 Variables in survival models

Some controls have been found to affect new venture survival in previous studies, specifically in Hechavarría *et al.'* (2016) research. Among these controls, human capital related variables are those more important for this study since the current theoretical debate is between this occupation-based approach and the classical human capital approach, which focuses on the individual educational level. EDUC is the variable used here that measures the respondent's educational level. Since PSED-I only asks this information for the respondent, it is measured using a categorical variable that accounts for his/her level and not for the entire team. This categorical variable has the category high school degree or less as the base (=0), which is compared it with other four categories, first entrepreneurs who have finished a tech, community, or have some college studies (=1), those who finished college or some graduate training (=2), those holding a Master's degree, (=3), and those who have a Ph.D. degree (=4).

As mentioned previously, the creative class approach aims to measure what people do in their daily tasks instead of what they have studied. Thus, other variables aimed to measure the tacit knowledge of entrepreneurial teams have to be included. In this sense, INDXP is a variable that measures the number of years of experience for each owner in the same industry that the startup aims to operate. Similarly, STPXP, which is a variable that measures the number of prior start-up attempts for each team member since previous exposure to an entrepreneurial experience can reinforce positive attitudes towards it (McCann, 2017) can also provide the team with the implicit experience of being an entrepreneur. Both INDXP and STPXP are measured for each PSED wave; thus, it is a time-varying variable, and its fluctuation is caused by the number of new entrepreneurs joining or former members entrepreneurs leaving the startup project.

HNW is the entrepreneur's household net-worth, standardized using 2005 prices based on the recommendations of Reynolds and Curtin (2008); since this variable was asked only for the first PSED interview, it accounts only for the respondent's household net worth, similar to Frid, Wyman, and Coffey, (2016) and Frid, Wyman, Gartner, and Hechavarría (2016). Also, TOTFUND is the team's total funds invested in the startup regardless of the source. In addition, FUNPER is a variable that measures the personal funds invested as a percentage of the total funding invested. Frid, Wyman, Gartner, and Hecheverría (2016) found that the more personal funds invested in the startup, the higher the chances of obtaining external funds, which positively impact profitability (Gartner, Frid, and Alexander, 2012) and a subsequently potentially has a positive impact on startup survival.

TEAM measures the number of entrepreneurial team members (owners defined as either individuals or organizations) for each PSED wave. This variable is also included since it affects disengagement from the start-up process (Carroll and Hannan, 2000). However, the number of members does not necessarily have a relationship with the effort each put into the startup. Therefore, the variable SWE accounts for sweat equity, which is the team's total hours of work on the startup, for each PSED interview.

Demographics also affects survival. The variable MEN controls for the number of male entrepreneurs on the entrepreneurial teams (Fairlie and Robb, 2009), and WHITE accounts for the number of whites-Caucasians (Sabbaghi, 2018; Singh, Know, and Crump, 2008). The number of members on the entrepreneurial teams aged 18-24, 25–34, 35–44, 45–54, and 55–99 are controlled using specific variables for each range (AGE<25, AGE35-44, AGE45-54, AGE>54). These demographic controls vary with each PSED wave depending on the number of new entrepreneurs joining or former members leaving the startup project[30].

The variable GRW is the growth aspiration of the respondent entrepreneur, coded =1 when the entrepreneur wants his or her company to be "as large as possible" and =0 when entrepreneurs want to keep the project manageable "by self or with key employees." Over-optimism is an issue for firm founders, and sometimes it might lead them to underestimate the competition, impacting firm survival (Delmar and Shane, 2003). INNOV controls for the innovativeness of the start-up, measured as a categorical variable adapting Aldrich and Ruef's (2006) definition, labeled "0" when the start-up is a reproducer venture and "3" if the start-up is an innovator venture. Having a business plan is associated with firm survival during the entrepreneurial process (Liao and Gartner, 2006). Thus, BPLAN controls for having a plan or not, as well as for the type of business plan used for each PSED wave. This categorical variable ranged from 0 to 3, with 0 representing when the entrepreneurs did not develop a business plan, 1 when they have an unwritten plan, 2 when they have developed an informal plan, and 3 when they developed a formal written plan. Financial projections reduce uncertainty in highly uncertain markets (Cassar, 2009); thus, FPRO is a time-varying variable included labeled =1 when the entrepreneur reports have financial projections for each PSED interview and 0 otherwise.

The start-up principal economic activity (PRAC) is included to control for the effects of the economic sector. This variable is coded 0 when the startup expects to operate in the business service market, 1 in the extractive sectors, 2 in transforming sectors, 3 in consumer-oriented sectors, and 4 for other sectors. Lastly, conception lag is included, following the recommendation

[30] Unfortunately, PSED I asked age only for the five more important owners; thus, when one of these variables is "5" it means that there are five or more startup owners within that range. However, less than 0.05% of total PSED-I observations declared having more than 5 owners. In the case of PSED II, this number increases to 1.06%.

of Yang and Aldrich (2012), to account for left truncation when evaluating firm survival and creation using PSED, measuring the time in months between the first interview and the conception date.

3.6.2 Variables in employment and profitability models

In their paper estimating the effect of the entrepreneur's wealth on employment and future profits, Frid, Wyman, and Coffey (2016) used the PSED II dataset. Since this study combines PSED I and II, thus, the models for employment outcomes replicate as best as possible those used in Frid *et al*. (2016)[31]. Their variables TEAM, MEN, WHITE, INNOV, STPXP, and EDUC are included in the survival model developed here. In addition, as in Frid *et al*. (2016), HELPERS is a variable that counts the number of non-owner helpers since it can have an impact on the need to hire employees. The variable PFUND records personal funds invested in natural logarithms. This variable changes for each PSED interview, depending on the amount invested. MANG accounts for the team's managerial experience in years, measured only in the first interview, and thus, it is a fixed covariate. The variable STYPE controls for the type of startup, coded 0 = independent startups, 1 = takeover, 2 = franchise, 3 = marketing initiatives, 4 = sponsored new businesses, and 5 = others/no reply.

3.7 Models and estimation procedures

To test Hypothesis 1, the new venture's likelihood of disengaging is estimated using Cox regressions (Allison, 2014; Mills, 2014; Cox, 1972). Similarly, to test Hypothesis 2a, a series of Cox regressions estimate the likelihood of transitioning from own account work (entrepreneurial teams without personnel) to employer (entrepreneur teams with personnel). To test Hypotheses

[31] Community support is not available in PSED I, as well as Gainfully employed since only the respondent is asked about this variable in PSED I; thus, they are excluded for the controls.

2b, the number of employees hired (in logs) is regressed, and equations are estimated using a random-effects Tobit regression for panel data (Henningsen, 2010). Also, to test Hypothesis 3, a series of Cox regressions estimate the likelihood for a team to develop a profitable startup.

When Cox models are applied, this study adopts Allison's (2014) guidelines and the following modeling strategy. The probability that an entrepreneur experiences the event of interest in the interval from *t* to *t* + *s*, given that the entrepreneur was at "risk" at time *t*, is denoted *P(t, t + s)*. This probability is divided by *s*, which is the time interval, and if *s* is left to become smaller until the ratio reaches a limit, it is defined as the continuous-time hazard, denoted by *λ(t)*: F

$$\lambda(t) = \lim_{s \to 0} \frac{P(t, t+s)}{s}$$

A basic Cox regression model explaining the continuous-time hazard for subject *i* is formally defined as

$$\lambda_i(t) = \lambda_0(t) e^{X_i\beta + X_i + \varphi}$$

where the baseline hazard function λ_0 is unspecified, but it is interpreted as the hazard function for subject *i* whose covariates all have the value of zero. For this reason, Cox models do not have an intercept term. The second part of the equation represents a linear function of an exponentiated set of *β* covariates, some of which them fixed and others time-varying. The *φ* coefficient is a continuous and time-varying variable measuring either the number of creative-entrepreneurs or the percentage of them among entrepreneurial teams, aimed to test Hypothesis 1, 2a, and 3.

Hypothesis 2b is evaluated by fitting a series of Tobit models since they are useful when an important percentage of observations have the value zero. In this study, using employment data as the dependent variable highlight the issue of having a high proportion of zero values (i.e., startups that never hired an employee). In this situation, parameter estimates obtained by conventional regression methods such as OLS are biased. The method proposed by Tobin (1958), commonly known as the Tobit provides consistent estimates in such settings. The standard Tobit model applied in this study, following Henningsen's (2010) recommendations, it is defined as

$$y^*_{i,t} = x'_{i,t-1}\beta + \varepsilon_{i,t-1} + \omega_i$$

$$y_{i,t}\begin{cases} 0 \; if \; y^*_{i,t} \leq 0 \\ y^*_{i,t} \; if \; y^*_{i,t} > 0 \end{cases}$$

where the subscript $i = 1 \ldots, n$, indicates the entrepreneurial team, and the subscript $t = 1, \ldots, n$, indicates time, specifically in this case the number of the interview the PSED dataset; $y^*_{i,t}$, is an unobserved or latent variable; $x'_{i,t}$ is a vector of independent variables; β a vector of unknown parameters; and $\varepsilon_{i,t}$ is the error term. As it is denoted, the independent variables were lagged in time *(t-1)*, using as explanatory variables the values of the previous PSED wave. While this research cannot inform about causality, at least it reduces as much as possible potential reverse causality issues between the dependent and the independent variables. Finally, for each entrepreneurial team *i*, there is a random effect that is shared and constant over time, represented in the ω_i coefficient. The variables are included in the same sequence as Liao and Gartner (2006), who created a base model that includes the control variables first and then introduce the primary independent variable of interest. Survival (Therneau and Lumley, 2015) and censReg (Henningsen, 2010) packages are used for model estimation here, using the R version 3.5.2

4. RESULTS

4.1 Descriptive statistics

The mean of the performance variables evaluated by entrepreneurial teams with either none or at least one creative entrepreneur can be seen in Table 2. The first outcome variable is the time from conception to disengagement from the entrepreneurial process, measured by the time in months from conception until its abandonment, i.e., when the entrepreneur reports that no one is any longer working on the startup project.

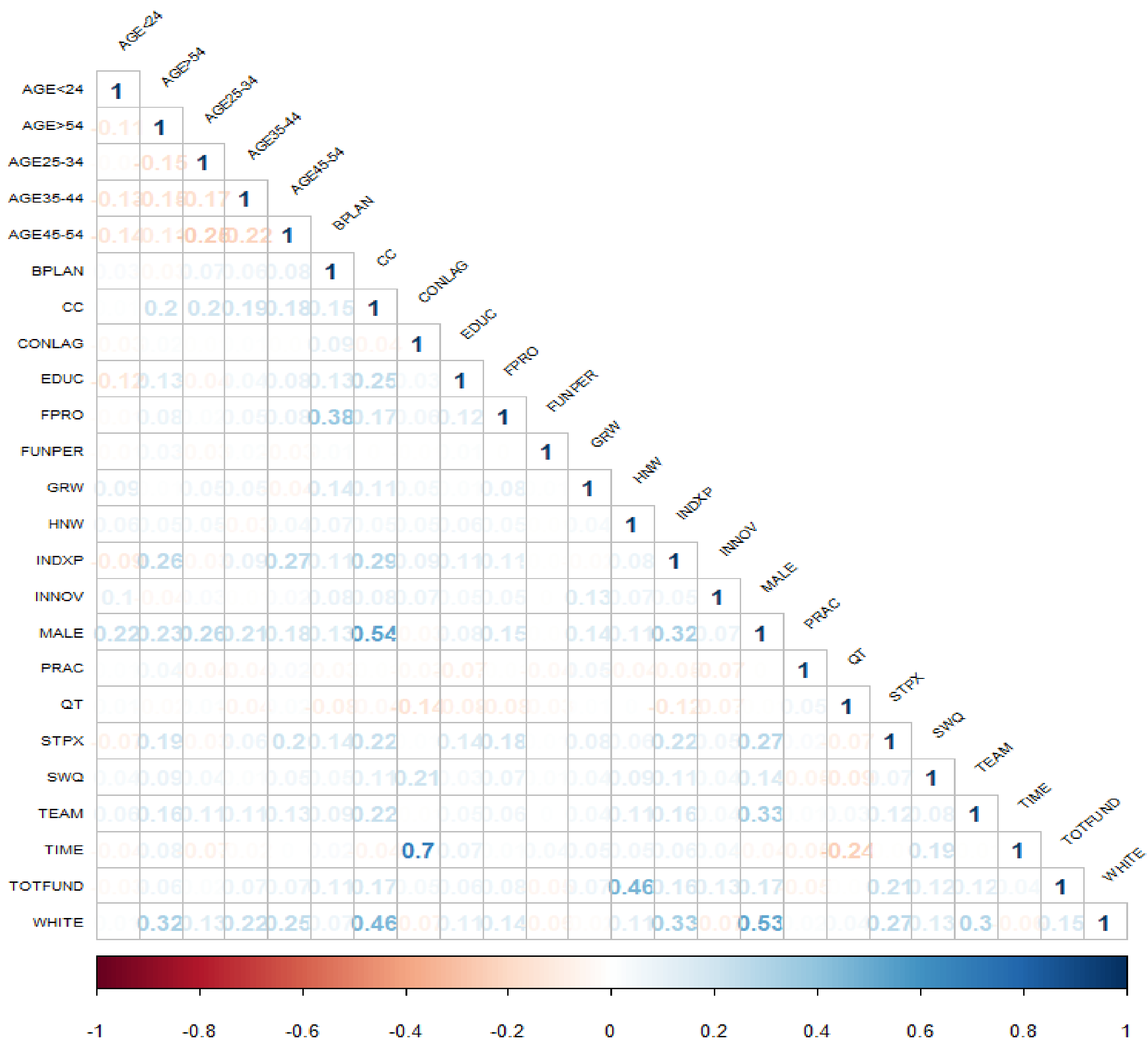
Table 2 – Outcome variables by entrepreneurial teams with and without creative owners

	Months to disengage from the entrepreneurial process	Months to first employee hired	Mean number of employees hired	Months to six months of profitability in a row
No creative member	34.8	22.3	0.9	31.3
At least one creative member	33.9	21.1	5.1	27.7

By analyzing the raw data from 1,599 cases without taking into account control variables, right-censoring, or nonlinearity treatment, it is possible to see differences among entrepreneurial teams with one creative entrepreneur compared to those who have none. Unexpectedly, teams with creative members show a shorter mean time to disengagement than those with no creative members. On the other hand, entrepreneurial teams with at least one creative member are more likely to reach profitability with their new venture projects and hire employees faster and in higher numbers. This previous data should be carefully considered. Table 2 is provided only to show that there are potential effects based on the number of creative entrepreneurs on new venture performance that could be worth investigating. To examine these possible associations, a comprehensive analysis of the outcome variables helps to address the right-censored in all event-history analyses and to address heterogeneity issues as well in the case of random Tobit models. A random-effect model was chosen because it allows estimation of the effects of time-invariant determinants. Including a random effect is especially important in this research since human capital variables, such as the creative background or the educational attainment vary little with time.

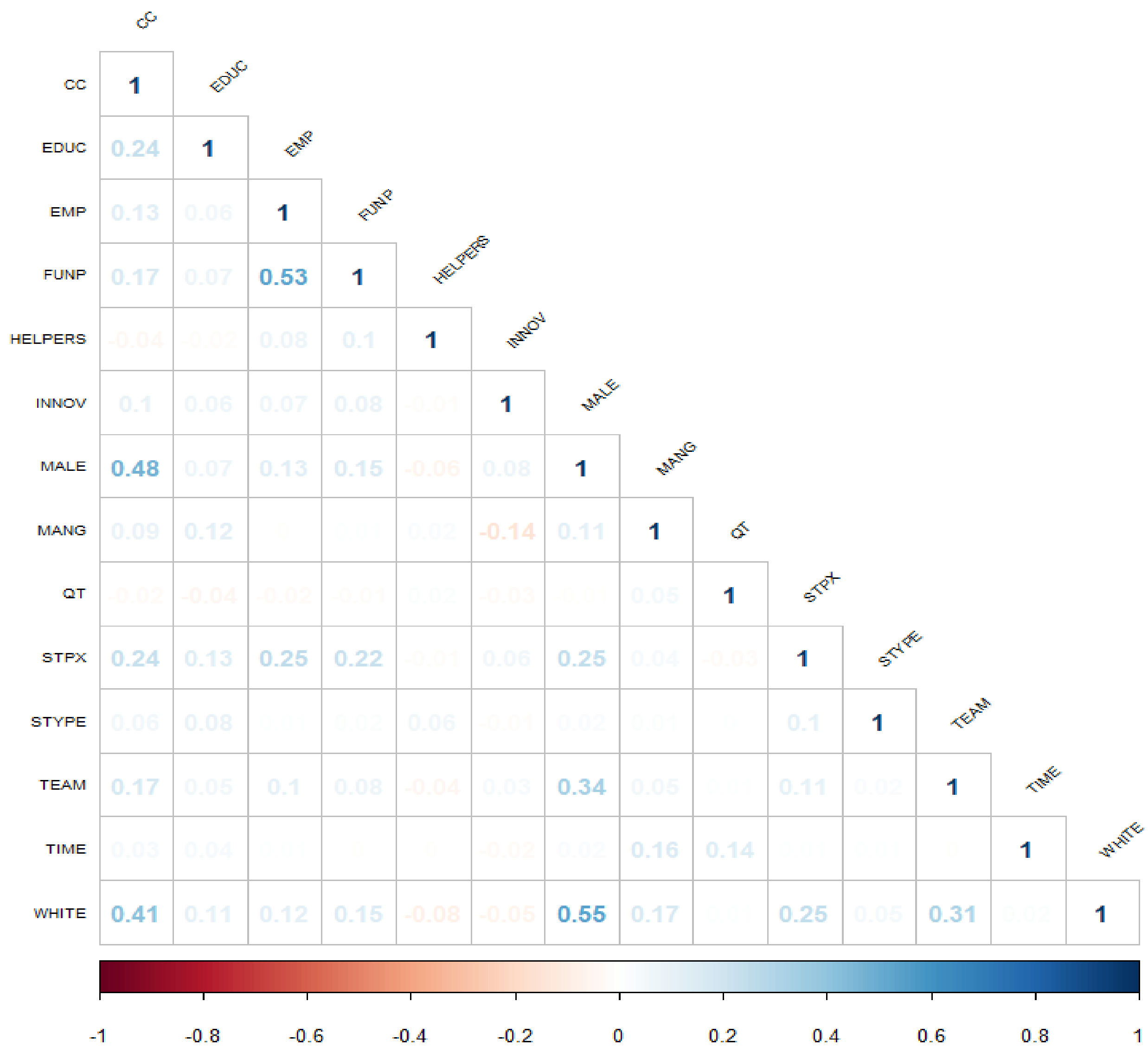
Severe multicollinearity is not an issue for survival models developed here. Chart 1 shows a correlation matrix for the variables included in the survival models, but only the first PSED interview given the unbalanced nature of the dataset. The only case of concern is the high correlation found between time and conception lag (0.7). Including CONLAG in the Cox regression could result in a violation of the proportional hazard assumption. A special treatment for this issue based on Alisson's (2014) recommendation, described in Section 4 for Models I, II, and III. The second coefficient of importance is between CC and MALE, which has a value of 0.54. The third most important is a Pearson correlation of 0.53 between MALES and WHITE.

Figure 1 - Correlation Matrix, Survival Models



Multicollinearity was not an issue when analyzing employment and profitability models. Again, by creating a correlation matrix of the first PSED interview using all variables of these models, it is possible to see that the highest Pearson correlation is 0.55 between MALE and WHITE. The second Pearson correlation in order of importance is between FUNP and EMP.

Figure 2 - Correlation Matrix, Employment Models



Therefore, in both cases, an acceptable amount of remaining variation allows this study to identify significant effects for the number of creative individuals among entrepreneurial teams. Thus, including the control variables benefit this research by reducing biases without great concern of multicollinearity.

4.2 Estimation results

Tables 3 to 6 provide the estimation results, where each table corresponds to one of the four outcomes of entrepreneurial performance. All tables show the results from four model variants. Three models help to evaluate each hypothesis. Models I, IV, VII, and X serve as a benchmark and include the only control variables. The second and third models test the hypotheses utilizing two measures of creative individuals at the startup level: (i) the number of creative individuals among the team in Models II, V, VIII, and XI, and (ii) the share of creatives on the team in Models III, VI, IX, and XII. The decision for including both measurements is to obtain more information about the absolute and relative measurements since solo projects composed 51% of the original PSED harmonized transition dataset.

Each specification is presented in a three-column format. The exponentiated coefficients and the 95% confidence intervals are shown for the survival models. Similarly, when evaluating the employment outcomes using the Tobit models including random effects, coefficients are reported with their 95% confidence intervals. Also, at the bottom of each table are the results of the likelihood ratio test, and for the survival models, the proportional hazard test. Results for each of the performance outcomes are reported in separate subsections below. In each subsection, first, findings related to the hypothesis are discussed, then the results concerning both creative entrepreneurs and educational variables, and finally, the results regarding control variables.

4.2.1 Firm Survival

Table 3 presents the empirical results. Model I evaluates firm survival, including the control variables. At least one of the covariates contributes significantly to the explanation of the duration of the events of interest since the likelihood-ratio chi-square statistic, which is the difference between -2 partial log-likelihood for the model with 32 covariates and the null model with no covariates, reveal a *p-value* <0.001. Thus, it is possible to reject the null hypothesis of the overall significance of the model. The proportional hazard assumption implied in any Cox model was met: Schoenfeld residual is = 0.51. This assumption was not met in the original model with no interaction term due to the variable CONLAG, and therefore is not shown here. For this reason, following Allison's (2014) and Mills' (2011) recommendation, an interaction was included between this variable and time, and then the proportional hazard assumption was met.

Table 3 presents the estimation results of the Cox regression for startup survival. The risk considered is disengaging from the entrepreneurial process. To test Hypothesis 1, Models II to III focus first on the number of creatives and the percentage of creative individuals' effect within entrepreneurial teams. Both Models II and III contribute at least one covariate that significantly explains survival duration. The results from Model II reveal that the rate of disengagement decreases 13% for each additional creative member on the start-up team. Model III indicates a similar pattern, meaning that for an additional 1% increase in the percentage of creatives in the startup team, the rate of disengagement decreases 0.1%. However, it is good to bear in mind that an actual 1% increase of creative-entrepreneurs among startup owners is unlikely. The addition of one creative owner will increase the percentage of creatives-entrepreneurs significantly more than 1%, since the maximum number of team members is fifteen (see Appendix F). However, this result should be taken with caution since it is only significant at the 90% level.

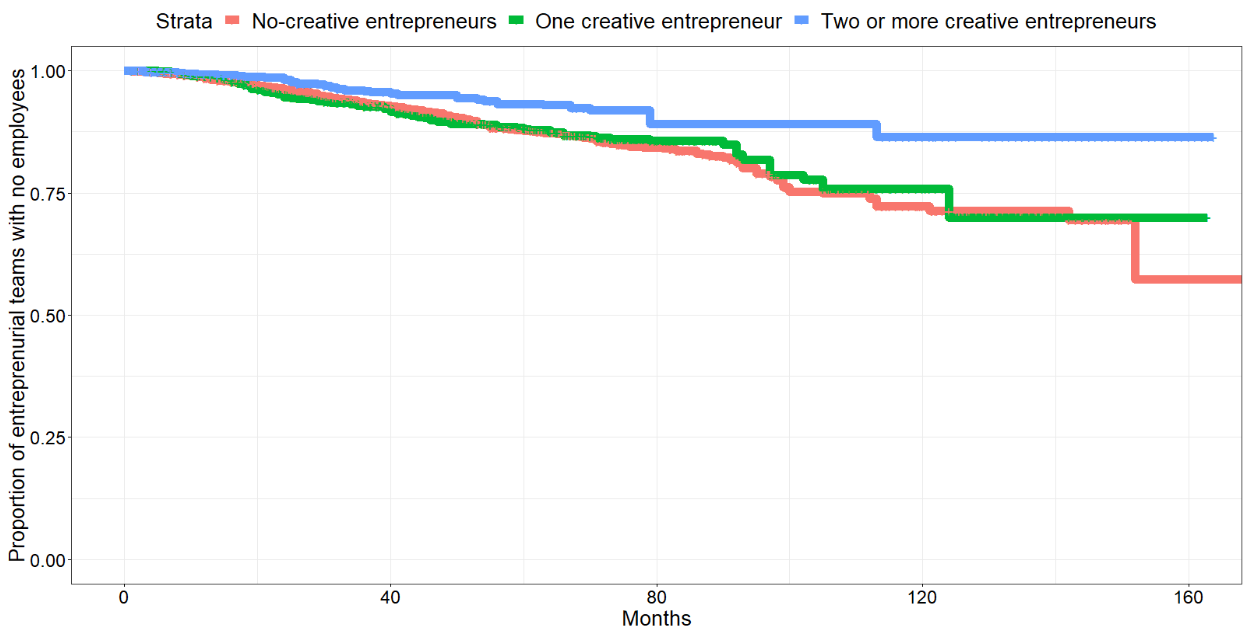
Table 3 – Cox Regression Models, Start-up Survival Analysis

	MODEL I: Cox regression model (disengagement)			**MODEL II: Cox regression model (disengagement)**			**MODEL III: Cox regression model (disengagement)**		
	Exp (coef)	**Lower .95**	**Upper .95**	**Exp (coef)**	**Lower .95**	**Upper .95**	**Exp (coef)**	**Lower .95**	**Upper .95**
CCE				***0.87****	***0.76***	***0.97***			
CC%							***0.99***$^{+}$	***0.99***	***1.01***
EDUC,									
base: high school degree or less									
Tech, community, or some college	0.78*	0.63	0.95	0.79*	0.64	0.97	0.78*	0.64	0.96
College or some graduate training	0.95	0.76	1.18	1.00	0.80	1.25	0.99	0.79	1.23
Master's degree	0.69*	0.49	0.98	0.72^{+}	0.51	1.02	0.71^{+}	0.50	1.00
PhD degree	0.54*	0.31	0.95	0.59^{+}	0.34	1.02	0.57^{+}	0.32	1.00
INDXP	0.99***	0.98	0.99	0.99**	0.98	1.00	0.98**	0.98	0.99
STPXP	0.99	0.95	1.03	0.99	0.95	1.03	0.98	0.95	1.02
MEN	1.00	0.88	1.12	1.02	0.90	1.16	1.00	0.88	1.13
WHITE	1.06^{+}	0.99	1.14	1.06^{+}	1.00	1.14	1.06^{+}	0.99	1.13
AGE<24	1.02	0.84	1.23	1.03	0.85	1.24	1.01	0.83	1.21
AGE25-34	1.25**	1.09	1.44	1.29**	1.12	1.48	1.25**	1.09	1.44
AGE35-44	1.05	0.90	1.22	1.07	0.92	1.24	1.05	0.90	1.22
AGE45-54	1.11	0.95	1.30	1.12	0.95	1.31	1.10	0.94	1.29
AGE>54	0.93	0.79	1.09	0.93	0.79	1.09	0.92	0.78	1.08
HNW	1.01*	1.00	1.00	1.01*	1.00	1.00	1.01^{+}	1.00	1.00
TEAM	1.01	0.98	1.02	1.00	0.98	1.02	1.01	0.98	1.02
SWQ	0.99*	0.99	1.00	0.99*	0.99	1.00	0.99*	0.99	1.00
GRW, *base: as large as possible =1*	1.15	0.96	1.39	1.16	0.96	1.40	1.16	0.96	1.40
INNOV, *base = 0*									
Degree of innovativeness= 1	0.93	0.78	1.12	0.93	0.78	1.12	0.93	0.77	1.11
Degree of innovativeness= 2	0.92	0.73	1.16	0.93	0.74	1.18	0.92	0.73	1.16
Degree of innovativeness= 3	0.84	0.59	1.22	0.86	0.60	1.24	0.85*	0.59	1.23
BPLAN,									
base: no business plan = 0									
Unwritten business plan=1	0.86	0.57	1.29	0.86	0.57	1.29	0.86	0.57	1.29
Informal business plan=2	0.83	0.61	1.13	0.84	0.62	1.15	0.84	0.61	1.14
Formally written business plan=3	0.65*	0.43	0.97	0.66*	0.44	0.99	0.64	0.43	0.97
FPRO, *"have financial projections"=1*	1.44**	1.12	1.84	1.46**	1.14	1.86	1.45**	1.13	1.85
PRAC, business service sector, base									
Extractive sector	0.96	0.60	1.53	0.94	0.59	1.50	0.94	0.59	1.51
Transforming sectors	1.22^{+}	0.97	1.52	1.22^{+}	0.98	1.53	1.22^{+}	0.98	1.53
Consumer oriented sectors	1.08	0.91	1.30	1.10	0.92	1.32	1.09	0.91	1.31
Other sectors/NA	0.98	0.37	2.59	0.93	0.35	2.47	0.93	0.35	2.48
TOTFUND	0.99**	0.99	0.99	0.99**	0.99	0.99	0.99**	0.99	0.99
FUNPER	0.98***	0.98	0.98	0.98***	0.98	0.98	0.98***	0.97	0.98
CONLAG	0.94***	0.93	0.95	0.94***	0.93	0.95	0.94***	0.93	0.95
CONLAG*TIME	1.00***	1.00	1.00	1.00***	1.00	1.00	1.01***	1.00	1.01
Likelihood ratio χ^2	783.4***, on 32 df			789.4***, on 33 df			787.3***, on 33df		
Proportional Hazard test	p-value = 0.52			p-value = 0.61			p-value = 0.58		

****p <0.001, **p <0.01, *p <0.05, $^{+}$p <0.1*

In Chart 3, the number 1 on the y-axis represents the total number of entrepreneurial teams in the sample which are at risk of disengagement, and the x-axis represents the time in months. Any reduction from 1 means a startup disengaged from the entrepreneurial process. The survival curve indicates that entrepreneurial teams with two or more creative entrepreneurs experience this event at a lower rate than those with one or zero creative entrepreneurs[32]. Entrepreneurial teams with none or one creative owner behave similarly in terms of disengagement. The results from the Cox estimations and the survival curve supports Hypothesis 1 that having more creatives among entrepreneurial team members extends firm survival.

Figure 3- Start-up Survival curve, stratified by the number of creative entrepreneurs in teams



The educational control variables show a stronger effect before including the CCE and CC%. For example, in Model I, EDUC is a categorical variable that reveals the odds of experiencing disengagement for each category compared with the base category (high school degree or less); three of four EDUC categories were significant in reducing the likelihood of disengagement compared to those entrepreneurs who have a high school degree or less. After including CCE and CC% in Model II and III, only one of the EDUC categories describing the entrepreneurs with a tech, community, or some college background remained significant in

[32] The last also confirms the results shown in Model II. Since the number of creative entrepreneurs in teams ranges from 0 to 10, plotting survival curve for each number would be illegible. For that reason, CCE has been re-codified to plot the survival curves into three categories. First, no creative entrepreneurs in the team, second, one creative entrepreneur, and finally, two or more creative entrepreneurs in the startup.

reducing disengagement when compared to the base category. Similarly, for each year of the team's industry experience, disengagement is reduced by 1.2%. This result was significant at the 0.1% level in Model I, but after the creatives variables are entered in Model II and III, its significance decreased to 99%, as well as the power of the coefficients to 1%. Previous startup experience shows no statistical significance in Models I to III.

Other control variables contributing to explaining disengagement and did not vary after entering CCE and CC%. For example, as the percentage of personal funds in total funds increases by 1%, disengagement is reduced by 2% for Models I to III. As expected, the total funds invested and entrepreneurs' household net worth, show a similar effect in reducing disengagement for all models. The effects of having financial projections and business plans did not vary in Models I to III either. However, having a financial projection increases the disengagement likelihood by 30%. This unexpected result could be explained because entrepreneurs with financial projections can monitor and forecast economic performance, meaning they can anticipate a decision to disengage as appropriate. Entrepreneurs that have a formal written business plan increase the likelihood of startup survival compared to those who do not have one. Having additional entrepreneurs between the ages of 25 and 34 decreases disengagement likelihood. Also, a small but significant effect is shown by sweat equity, which reduces disengagement slightly.

4.2.2 Transition from own account to employer

Table 4 shows results for the outcome measure "transitions from own-account worker to employer." Model IV evaluates the event of hiring the first employee, including the control variables. At least one of the covariates contributes significantly in explaining the duration of the events of interest since the likelihood-ratio chi-square statistic, which is the difference between -2 partial log-likelihood for the model with 21 covariates and the null model with no covariates, indicates a *p*-value <0.001, allowing the rejection of the null hypothesis of the model's overall significance. The proportional hazard assumption implied in a Cox model was met: the Schoenfeld residual is > 0.53. It was not possible to meet this assumption an original model which is not shown here, due to the variable QT, and therefore, again based on Allison (2014) and Mills (2011) recommendations, an interaction was included between this variable and time, resulting in meeting the proportional hazard assumption.

Concerning the role of creative-entrepreneur in hiring their first employee, the result is the relatively stable positive effect of the number of creatives. At the 0.1% significance level, the results in Model V show that the likelihood of hiring the first employee increases by 20% for each additional creative member on the start-up team. The percentage of creatives in the team shows a more robust significance in Model VI, where the exponentiated coefficient accounts for a 0.1% significance level. Regarding the magnitude of the effect, the results in Model VI reveal that holding other variables constant, an increase of 1% in creatives is associated with an increase in the "hazard" of hiring the first employee by 0.5%.

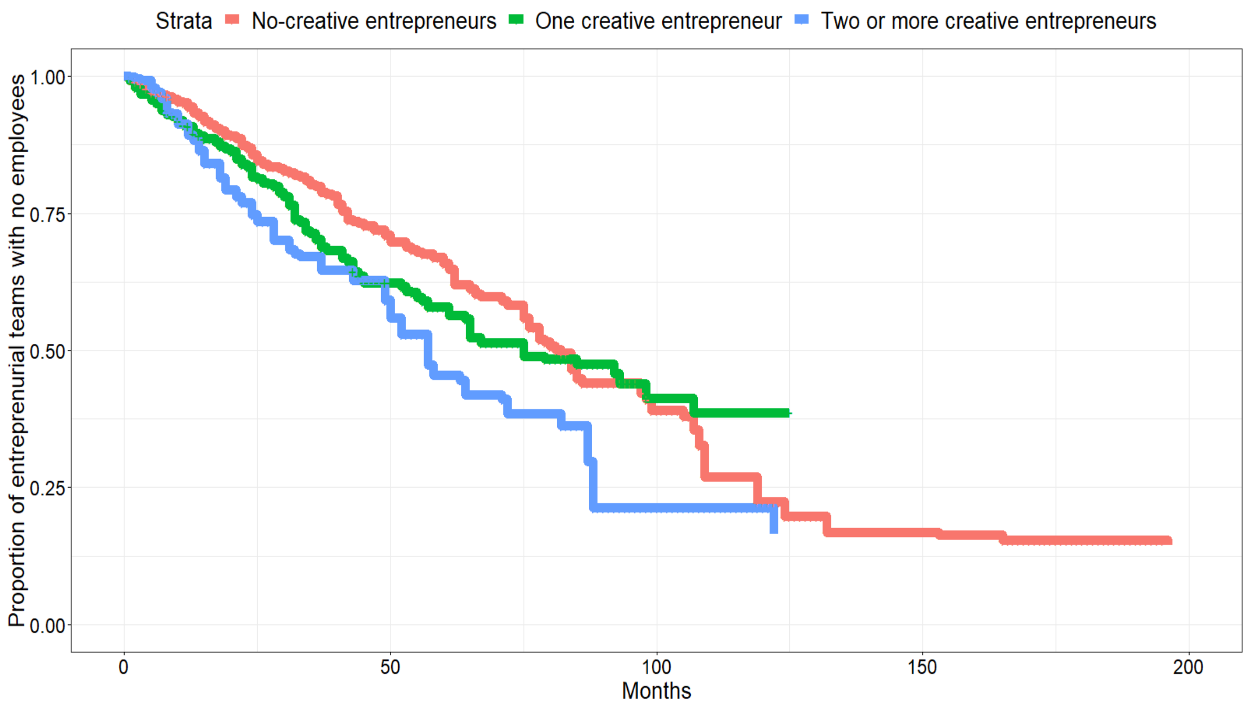
Table 4 – Cox Regression Models, Analysis of the Time to Hire the First Employee

	MODEL IV: Cox regression model (first worker)			MODEL V: Cox regression model (first worker)			MODEL VI: Cox regression model (first worker)		
	Exp (coef)	**Lower .95**	**Upper .95**	**Exp (coef)**	**Lower .95**	**Upper .95**	**Exp (coef)**	**Lower .95**	**Upper .95**
CCE				***1.20*****	***01.05***	***1.37***			
CC%							**1.01*****	***1.00***	***1.01***
EDUC, base: high school degree or less									
Tech, community, or some college	1.12	*0.86*	*1.47*	1.09	*0.83*	*1.43*	1.09	*0.83*	*1.43*
College or some graduate training	1.21	*0.91*	*1.60*	1.08	*0.80*	*1.45*	1.06	*0.79*	*1.42*
Master's degree	1.37^{+}	*0.95*	*1.99*	1.26	*0.85*	*1.85*	1.28	*0.87*	*1.88*
PhD degree	1.33	*0.81*	*2.20*	1.25	*0.75*	*2.11*	1.23	*0.73*	*2.07*
STPXP	1.01*	*1.00*	*1.02*	1.04**	*1.01*	*1.08*	1.04**	*0.98*	*0.99*
MANG	0.99	*0.99*	*1.00*	0.99^{+}	*0.98*	*1.00*	0.99*	*0.98*	*0.99*
WHITE	1.05^{+}	*0.99*	*1.12*	1.03	*0.96*	*1.10*	1.03	*0.96*	*1.10*
MALE	1.08	*0.97*	*1.19*	1.08	*0.94*	*1.25*	1.10	*0.95*	*1.26*
TEAM	1.00	*0.95*	*1.04*	0.89	*0.78*	*1.02*	1.05	*0.98*	*1.12*
HELPRES	1.06^{+}	*1.00*	*1.12*	1.05^{+}	*0.98*	*1.11*	1.06^{+}	*1.00*	*1.13*
PFUND(log)	1.13***	*1.11*	*1.16*	1.13***	*1.11*	*1.16*	1.13***	*1.11*	*1.16*
INNOV, base = 0									
Degree of innovativeness= 1	0.87	*0.69*	*1.10*	0.85	*0.66*	*1.05*	0.85	*0.67*	*1.07*
Degree of innovativeness= 2	0.82	*0.62*	*1.10*	0.72*	*0.52*	*0.98*	0.75^{+}	*0.55*	*1.01*
Degree of innovativeness= 3	0.78	*0.51*	*1.21*	0.77	*0.47*	*1.25*	0.77	*0.47*	*1.25*
STYPE, base = independent startups									
takeover = 1	2.22***	*1.43*	*3.46*	2.22***	*1.41*	*3.44*	2.24***	*1.43*	*3.51*
franchise = 2	1.01	*0.59*	*1.71*	0.99	*0.54*	*1.59*	0.92	*0.54*	*1.58*
marketing initiatives = 3	1.08	*0.51*	*2.27*	1.05	*0.49*	*2.22*	1.01	*0.448*	*2.14*
sponsored new business = 4	1.89***	*1.35*	*2.66*	1.81***	*1.28*	*2.55*	1.78***	*1.26*	*2.52*
Others = 5	0.77	*0.23*	*2.57*	0.72	*0.23*	*2.56*	0.72	*0.21*	*2.42*
QT	6.27***	*3.71*	*10.59*	6.67***	*3.93*	*11.3*	6.63***	*3.91*	*11.24*
QT*TIME	1.03***	*1.02*	*1.04*	1.03***	*1.01*	*1.04*	1.03***	*1.01*	*1.04*
Likelihood ratio χ^2	620.3, on 21 df			599.9, on 22 df			602.8, on 22 df		
Proportional Hazard test	0.53			0.58			0.55		

****p <0.001, **p <0.01, *p <0.05, $^{+}$p <0.1*

In Chart 4, the number 1 represents the total entrepreneurial teams, and any reduction from 1 means a startup transitioned from not having any employees to employing its first worker. Based on these estimates, entrepreneurial teams with two or more creatives, as shown by the blue line, hire their first employee faster than those with one or zero. Interestingly, entrepreneurial teams with at least one creative-entrepreneur hire its first employee at similar rates to those with two or more at the beginning of the entrepreneurial process. However, as time passes, entrepreneurial teams with one creative member, as shown by the green line, behave similarly to those with no creatives among the owners, as shown by the red line. It is also possible to see that only startups with no creative-entrepreneurs remain until the last month of observation without having hired one employee.

Figure 4 – Curve of the transition from own-account to employer, stratified by the number of creative entrepreneurs in teams



Similar to Models I to III, the entrepreneurial teams' educational variables are again affected when CCE and CC% are included. In transitioning from sole proprietorships to hiring the first employee, EDUC seems to have virtually no effect except for the category entrepreneurs holding a Master's degree. These entrepreneurs are 31% more likely to hire their first employee compared to entrepreneurs having a high school degree or less but only at the 10% level. This last effect disappears when both CCE and CC% are entered in Models V and VI, respectively. The variable STPX is significant at the 95% level in Model IV, but its significance increases to 99% after introducing CCE and CC% in Models V and VI. The power of the STPX coefficient increases after entering CCE and CC% as well. Before introducing these variables, for a yearly increase of startup experience, the "risk" of hiring the first employee also increases by 1%. After CCE and CC% were introduced, this risk increases to 4% for every additional year of team startup experience. These results also reveal a similar pattern for managerial years of experience (MANG). This variable exhibited a 90% significance level before CCE, and CC% were introduced. However, after the introduction of the creative variables in Models V and VI, its significance increases to 95% and 99%, respectively. In both models, an increase in the team's average years of managerial experience accounts for a small but decreasing "hazard" of hiring the first employee.

The coefficients of the control variables show that an increase in FUNP increases the "hazard" of employing the first worker. Two types of startups, takeover and sponsored businesses are associated with an increased "risk" of hiring the first employee. A shorter time to hiring the first employee is associated with QUIT as well because those startups that disengage were observed for a shorter period due to their exit. It is essential to control for this variable since it can bias the time if it is not included. All these effects of the control variables do not change significantly across Models IV to VI; the only exception been is the variable HELPERS. This variable is associated positively with the event of hiring the first employee, and it is significant at the 95% level before including the CCE and CC% in Model IV. After adding CCE and CC% in Models V and VI respectively, it is significant only at the 10% level.

4.2.3 Number of employees

Table 5 provides the result for the Tobit estimations. The coefficients capture the effect on the uncensored latent variable, not the observed outcome. Given that EMPlog is expressed in natural logarithms, these coefficients are interpreted as the percent change in the number of employees in the case of continuous variables. For dichotomous or categorical variables, the coefficients reflect the percent change in earnings for a discrete change in the category or from the change from 0 to 1 in the case of a dummy variable.

Table 5 presents the estimated results of the number of hired workers for every entrepreneurial project. Based on the log-likelihood, the inclusion of CCE and CC% improved the model fit. Model I accounts for a log-likelihood of -2640.1, while for Models VIII and IX, it was reduced to -2637.1, and -2637.9, respectively. According to Model VIII, as can be seen in Table 5, for an increase in the number of creative entrepreneurs by one individual, the expectation is an increase in the number of employees by 29%, holding other variables constant. This significant association is also found in Model IX when using CC%: An increase of just 1% of creative-entrepreneurs on the team is associated with 0.4% employment growth. Recall that a 1% increase in creative-entrepreneurs among startup owners is theoretical. Empirically it is unlikely to happen since just one additional creative owner on the team will have a higher impact than 1% because the maximum number of team owners is fifteen members.

Both results regarding CCE and CC% are significant at the 95% level. Thus, Hypothesis 2b is supported for both measures of creative individuals in entrepreneurial teams.

Table 5 – Tobit Regression Models, Number of Employees Hired

	MODEL VII: Tobit model (number of employees)			MODEL VIII: Tobit model (number of employees)			MODEL IX: Tobit model (number of employees)		
	Coef	**Lower .95**	**Upper .95**	**Coef**	**Lower .95**	**Upper .95**	**Coef**	**Lower .95**	**Upper .95**
Intercept	-4.48***	-5.16	-3.80	-4.32***	-5.02	-3.63	-4.42***	-5.09	-3.74
CCE				**0.29***	**0.07**	**0.52**			
CC%							**0.01***	**0.00**	**0.01**
EDUC, base: high school degree or less									
Tech, community, or some college	0.08	-0.38	0.54	-0.02	-0.48	0.43	0.01	-0.45	0.46
College or some graduate training	0.12	-0.37	0.62	-0.03	-0.53	0.47	-0.03	-0.53	0.47
Master's degree	0.01	-0.65	0.67	0.07	-0.57	0.71	-0.02	-0.67	0.63
PhD degree	1.33**	0.51	2.15	1.22**	0.43	2.02	1.23**	0.45	2.01
STPXP	0.03	-0.03	0.09	0.05^{+}	-0.01	0.10	0.04	-0.02	0.09
MANG	-0.02***	-0.03	-0.01	-0.02***	-0.03	-0.01	-0.02***	-0.03	-0.01
WHITE	0.10	-0.02	0.21	0.05	-0.07	0.17	0.08	-0.04	0.20
MALE	0.30	0.11	0.49	0.23	0.05	0.42	0.24	0.05	0.42
TEAM	0.04	-0.14	0.23	0.01	-0.16	0.19	0.07	-0.11	0.25
HELPRES	0.15***	0.09	0.20	0.14***	0.09	0.20	0.14***	0.09	0.20
PFUND	0.07***	0.05	0.10	0.07***	0.05	0.09	0.07***	0.05	0.10
INNOV, base = 0									
Degree of innovativeness= 1	0.32	-0.04	0.68	0.18	-0.18	0.54	0.29	-0.07	0.65
Degree of innovativeness= 2	0.05	-0.42	0.52	-0.07	-0.53	0.40	0.03	-0.43	0.49
Degree of innovativeness= 3	-0.38	-1.21	0.46	-0.55	-1.41	0.30	-0.45	-1.29	0.39
STYPE, base = independent startups									
takeover = 1	1.33***	0.61	2.04	1.33***	0.61	2.05	1.31***	0.57	2.04
franchise = 2	-0.36	-1.13	0.40	0.1	-0.58	0.78	-0.42	-1.21	0.38
marketing initiatives = 3	-0.17	-1.06	0.73	-0.15	-1.07	0.77	-0.2	-1.10	0.71
sponsored new business = 4	0.83	0.21	1.44	0.7	0.07	1.33	0.76	0.14	1.37
Others = 5	-0.90	-3.16	1.36	-0.92	-3.28	1.44	-0.88	-3.12	1.36
logSigmaMu	0.73	0.59	0.87	0.75	0.61	0.88	0.72	0.58	0.86
logSigmaNu	0.58	0.51	0.65	0.58	0.51	0.65	0.58	0.51	0.65
Log-Likelihood	-2640.1, on 22 df			-2637.1, on 23 df			-2637.9, on 23 df		

****p <0.001, **p <0.01, *p <0.05, +p <0.1*

The other human capital related variables show stable results in Models VII to IX. Concerning an entrepreneur's formal education, Model VIII suggests that entrepreneurs with a Ph.D. hire more than double the employees (132%) than entrepreneurs with a high-school degree or less, the only significant comparison among EDUC categories. After including CCE and CC% in Models VIII and IX, the coefficient power decreases slightly. Managerial experience is negatively associated with EMPlog. For a year increase in MANG, there is a reduction of 1.7% in the number of employees hired. When Models VIII and IX include CCE and CC% respectively, the MANG coefficient remained stable in its both significance and power. STPX never reached a 95% significance level in any of the Models VII to IX.

There is also a group of control variables associated with employment levels in Models VII, VIII, and IX. For example, MALE indicates a positive relationship between male entrepreneurs and the number of employees hired, an association found in all models. The variable HELPERS exhibited the same pattern: Having more external non-owner helpers increases the number of employees. The higher personal funds invested (FUNP variable), the higher the number of employees hired, an association found across the three models evaluating the number of employees. Finally, the type of startup is controlled using the STYPE categories. As was expected, takeover startups are associated with having more employees when compared to independent startups (the base category).

4.2.4 Six consecutive months of profit reported

Table 5 presents the results for the time it takes to become a profitable firm, defined as six consecutive months of profits. Specifically, Models IX to XI use the subsample of those companies that did not disengage from the entrepreneurial process. As a result, companies can either become profitable or are labeled as “still trying” to achieve profitability. In all models, at least one of the covariates contributes significantly to the explanation of the profitability event. The likelihood-ratio chi-square statistic, which is the difference between -2 partial log-likelihood for the Model X with 21 covariates and Models XI and XII with 22 covariates, and the null model with no covariates, reveals a *p*-value <0.001in for these three cases.

The results cannot confirm hypotheses 3a and 3b. Given the significance of the chi-square statistic, at least one of the covariates contributes significantly to the explanation of becoming a profitable startup in Models X, XI, and XII. However, after the introduction of CCE and CC%, the likelihood-ratio chi-square statistic did not improve in Models XI and XII. In addition, both variables are not statistically significant in any model.

Table 6 – Cox Regression Models, Analysis of the Time to Achieve a Sixth Months of Profits

	MODEL IX: Cox regression model (first worker)			MODEL X: Cox regression model (first worker)			MODEL XI: Cox regression model (first worker)		
	Exp (coef)	Lower .95	Upper .95	Exp (coef)	Lower .95	Upper .95	Exp (coef)	Lower .95	Upper .95
CCE				**1.08**	**0.94**	**1.23**			
CC%							**1.00**	**1.00**	**1.00**
EDUC, base: high school degree or less									
Tech, community, or some college	1.07	0.80	1.41	1.06	0.80	1.40	1.05	0.79	1.39
College or some graduate training	0.96	0.70	1.30	0.92	0.67	1.27	0.91	0.67	1.26
Master's degree	0.78	0.52	1.17	0.76	0.51	1.15	0.76	0.50	1.14
PhD degree	0.91	0.54	1.54	0.88	0.52	1.49	0.87	0.51	1.48
STPXP	1.01	0.99	1.01	1.01	0.99	1.02	1.01	0.99	1.02
MANG	0.99	0.99	1.01	0.99	0.99	1.00	1.00	0.99	1.00
WHITE	1.09*	1.01	1.17	1.08*	1.00	1.16	1.08*	1.01	1.17
MALE	1.11^{+}	0.98	1.25	1.08	0.95	1.23	1.09	0.97	1.23
TEAM	1.00	0.93	1.07	1.00	0.94	1.08	1.01	0.94	1.08
HELPRES	1.07*	0.97	1.114	1.07	1.01	1.14	1.07	1.01	1.14
PFUND	0.99	0.97	1.01	1.00*	0.97	1.02	1.00*	0.97	1.02
INNOV, base = 0									
Degree of innovativeness= 1	0.95	0.75	1.20	0.94	0.74	1.19	0.95	0.75	1.20
Degree of innovativeness= 2	1.08	0.83	1.43	1.07	0.82	1.41	1.08	0.82	1.41
Degree of innovativeness= 3	0.82	0.52	1.28	0.80	0.51	1.26	0.81	0.52	1.26
STYPE, base = independent startups									
takeover = 1	1.37	0.84	2.25	1.40	0.85	2.29	1.41	0.86	2.30
franchise = 2	0.99	0.58	1.66	0.99	0.58	1.66	0.98	0.58	1.65
marketing initiatives = 3	0.82	0.39	1.73	0.82	0.39	1.73	0.81	0.39	1.70
sponsored new business = 4	1.70**	1.23	2.36	1.69**	1.22	2.35	1.70**	1.23	2.36
Others = 5	0.84	0.31	2.26	0.85	0.32	2.29	0.85	0.32	2.30
CONLAG	0.96***	0.95	0.97	1.06***	0.93	1.23	1.00***	0.99	1.00
CONLAG*TIME	1.01***	0.99	1.05	1.01***	1.00	1.01	1.00***	1.00	1.00
Likelihood ratio χ^2	126, on 21 df			127.2, on 22 df			127.5, on 22 df		
Proportional Hazard test	0.26			0.25			0.26		

****p <0.001, **p <0.01, *p <0.05, $^{+}$p <0.1*

Unexpectedly, neither of the educational variables shows any effect on profitability. Regarding the remaining control variables included, the variable HELPERS indicates that having more helpers shows a positive and significant relationship with profitability, as well as the number of whites/Caucasians in entrepreneurial teams. As expected, among the categories of STYPE, sponsored new business is the only category that accounts for a significant effect when compared to independent startups (the base category) in Models X to XII.

4.2.5 Summary of the primary results

The primary results from Tables 3 to 6 can be summarized as follows. Better startups performance outcomes during the gestational phase are expected in entrepreneurial teams led by creative teams. This result is especially true when more than one creative entrepreneur leads the team. Having more creatives among startup owners increases the survival chances of the new venture. Also, there is a positive impact on the transition time from a startup without personnel to the hire of the first employee. Similarly, an entrepreneurial project owned by a higher number of creative individuals is positively related to the number of employees hired. Most of the analyses of this study indicated that when evaluating startup performance outcomes, variables measuring the entrepreneurs' creative background outperform the standard educational attainment measurements. However, this study did not find a relationship between having more creatives owners among teammates and startup profitability.

5. DISCUSSION

Human capital obtained through education is one of the most reliable drivers of entrepreneurship performance at the firm level. However, this standard measurement of human capital has been questioned at the regional level by Florida's CCT in many studies related to entrepreneurship and economic development. More specifically, Florida *et al.* (2008) research found that formal education positively impacts gross product and wealth, while creative-class related variables are strongly associated with employment and wage growth at the regional level. In this study, the firm level is the scope of the analysis. This study examined whether having a higher number of creative individuals on entrepreneurial teams improves startup performance, finding that there are micro-level fundaments for the macro-level findings of Florida *et al.* (2008): More creative-entrepreneur-owned startups are strongly associated with job creation. This research also provides new results on the relationship between creative-entrepreneurs and the length of startup survival times.

Specifically, this research found support for a positive relationship between having more creative-entrepreneurs as owners and three of the four measures of startup success considered — survival, the transition from not having any to the hire of the first employee, and the number of employees hired. Regarding new venture survival, companies led by creatives might seek to operate in new and niche markets. Consequently, their survival chances increase because they face low competition levels (Kim and Mauborgne, 2014). In addition, innovative entrepreneurs exhibit higher survival chances since the demand for new innovative products and services increases consumers' growing wealth (Jackson, 1984). As described by CCT, creatives are innovative, problem-solving individuals, and their startups might be as well. However, one limitation of this study is not considering the markets where startups operate. Future research will have to consider the regional dimension interacting with the startup factors, and the regional variables to analyze firm survival. As mentioned previously, this study found that projects led by more creative entrepreneurs tend to survive longer, but it did not investigate whether it is an effect of operating in more sophisticated markets or not.

The more robust relations found in this study are between the creative-entrepreneur's variables and employment creation. Both the transition from not having employees to hiring the first worker and the startup's number of employees are positively associated with the number of creative-entrepreneurs as owners. As mentioned above, Florida *et al.* (2008) research found that creative-class related variables are strongly associated with employment and wage growth at the regional level. It is not possible to make the same argument based on this study since PSED does not provide information about employee's wages. This topic should be investigated using a dataset that contains the salaries provided by creative-led startups. However, at the startup micro-level, this study found that creative-led startups hire employees faster and at higher numbers, supporting past results found at the macro-regional level.

6. CONCLUSIONS, POLICY IMPLICATIONS AND FUTURE RSEARCH

Human capital is a measurement of the knowledge that individuals possess. Knowledge for entrepreneurship matters. The policy implication of this study is to broaden the concept of knowledge applied to entrepreneurship. Education can be viewed and is used as a direct instrument for developing entrepreneurship behavior. However, highly educated individuals do not necessarily have the highest entrepreneurial ability. In this regard, non-mainstream human capital measurements such as the number of creative individuals helped in identifying these individuals. Creative individuals possess tacit knowledge that is difficult to measure through the standard human capital variables commonly used in entrepreneurship research. This idea is also reinforced since measurements such as the team's years of industry experience, managerial experience, and previous startups attempts were more impactful compared to the education variables on the outcomes tested in this study.

This first step in investigating creative entrepreneurs at the firm level highlights many avenues of future research. For example, future research can examine how each sub-group of the creative class influences new venture performance. Does, the super-creative core impact new venture performance in the same manner that creative professionals or bohemians do? What's the role of the composition of entrepreneurial teams within the creative class subcategories? For example, do teams composed of the super-creative, creative-professionals, and bohemians perform better than teams composed only of super-creatives? All these questions can be analyzed using PSED or other available entrepreneurship datasets.

Data from PSED I and II were used to provide new evidence on entrepreneurs' characteristics associated with startup outcomes. Overall, as similar to the previous research about entrepreneurial development at the regional level, the findings from this study challenge the standard measurement of human capital through educational attainment. The creative entrepreneurs' measurements significantly explained three of the four performance outcomes tested in this research. Thus, the previous working background is important for entrepreneurship, especially on entrepreneurial teams in which members had a creative occupation before starting a new company. Therefore, policies targeted to support people in creative professions to join and move towards entrepreneurship could benefit economic development, especially in employment deprived areas.

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CONCLUSIONS

The articles comprising this dissertation extend on the current state of entrepreneurship research, by applying theories and methodologies, while having being applied extensively in other domains, are novel to this field. Based on these three research articles, it is possible to find out the interdisciplinary nature of entrepreneurship research (Acs and Audretsch, 2003) and the need for embracing as many fields as possible in order to recommended policies for the current economy in this area. Therefore, the concluding remarks of this dissertation highlight what is new in the field of entrepreneurship research as a result of these three pieces of research by looking at three dimensions: the theory, the methods, and the policy recommendations resulting from each of the three articles.

In the first article, the theory applied is the classical human capital approach used to investigated firms in the developed world. However, few studies have applied this traditional human capital approach to developing regions, especially Latin America. As is discussed, contextualization is needed when investigating innovation, because what is new in one place may not be a novelty in others. For that reason, the theoretical innovation of the first paper is incremental, applying a well-known theory in a particular context that was not used before to investigate entrepreneurship topics.

Methodologically, the paper uses a unique panel dataset to investigate the innovation behavior of companies in Uruguay at the firm level. The logit model with time-fixed effects allowed this research to control for firms’ time-invariant unobservable characteristics while providing a rich set of time-varying observable characteristics. In addition, the inclusion of interaction effects between the human capital variables and the size of the companies allowed this study to examine the effects of these variables on different types of companies. Based on this technique, this research found variations on how three human capital dimensions impact differently depending on the size of the companies.

This research found that human capital is associated with product innovation, but as mentioned, not all types of human capital functions in the same way for all companies. Increasing the number of educated employees fosters the likelihood of product innovation for small firms, this analysis indicating that it is not possible to examine human capital dimensions in a vacuum. In Uruguay, the economy investigated in the first paper, the number of firms with no educated workers grew during the period of study, as did the number of small and mid-sized manufacturing firms with no professionals. Thus, public policy to foster product innovation by hiring educated workers in Uruguayan manufacturing firms has to target small firms. If small firms increase their number of skilled workers, it is possible to increase to some extent the innovative capacity of the Uruguayan manufacturing industry. However, for large firms, policies aimed to increase the number of educated employees will not have an impact because having more professionals can result in a negative effect.

However, for large firms increasing the investment in internal training for employees was found to be an essential factor for improving their product innovation likelihood, something not found for small companies. Taking into account that the vast majority of policies aimed to foster innovation in Uruguay through human capital focuses on hiring more professionals or providing post-graduate studies for the firm’s employees, the results support a change in the targeting strategy. While the policies focusing on formal education would have a positive impact on small companies, large companies require policies targeting internal training.

The second article applied the Matthew effect theory, which was initially designed to explain cumulative advantages of agents in a wide range of domains, including science, technology, and society studies, but also in sociology, education studies, and public policy, to mention a few. Using this theory to investigate entrepreneurship finance shed light on a potential cumulative advantage in the entrepreneurial reward system, specifically the financing system. Previous research identified the latter, studying specific dimensions such as wealth, race, or social connections. Applying the Matthew effect theory allows the study to determine the critical factors for obtaining receive funding recurrently. This theory help to identify how structural factors such as personal income or social capital influence receiving external funding. However, other factors associated with the actions that entrepreneurs can take impact on obtaining external financing as well.

Methodologically, this second paper applied innovative models. Several advances result from the use of PSED to investigate the entrepreneurship process (Shim and Davidsson, 2018; Reynolds, 2017; Gartner and Shaver, 2012; Yang and Aldrich, 2012; Reynolds, Gartner, Greene, Cox, and Carter, 2008). However, very few studies took advantage of the time trends of this project, specifically, those that applied event history analysis (Frid, Wyman, and Coffey, 2016; Hechavarría, Matthews, and Reynolds, 2016; Brush, Manolova, and Edelman, 2008; Delmar and Shane, 2003). This study continues to fill this gap by taking advantage of the time trends available in the PSED project and applying event history analysis to analyze firm creation, survival, and financing. Specifically, to examine the latter, a series of Cox regressions with a frailty component were applied, allowed us to analyze external funding as a repeated event. The last technique is a novelty in the field since previous studies considered only the first funding event while the models applied here considered all funding events during the entrepreneurial gestational phase.

The modeling strategy resulted in unique findings and, thus, new policy recommendations. First, they highlight the importance of obtaining external funding more than once as a critical determinant for a firm's survival and creation. The Cox regressions for repeated events applied here identified structural factors such as wealth and specific dimensions of social capital that influence receiving external monitored funding. Specifically, wealthier entrepreneurs have shorter time gaps between each external funding event than their less affluent counterparts. Similarly, the teams' years of managerial experience are positively associated with reducing gap times in receiving external funding. In addition, specific actions that entrepreneurs take can reduce gap times in getting funded as well, such as defining a business plan or developing having financial projections.

However, the modeling strategy of this study, which considered all funding events during gestation, resulted in findings that question previous structural factors associated with receiving funding. For example, this study found evidence that race, which has been mentioned as a critical factor in explaining receiving monitored funding (Frid, Wyman, Gartner, and Hechavarría, 2016; Frid, 2014; Gartner, Frid, and Alexander, 2012), was not a critical factor associated with recurrent external monitored funding. Race as a variable, specifically being part of a minority group, could be an inhibitor for minority-owned startups for obtaining their first external funding due to discrimination or other social factors, but once funded for their first time, the effect of race as an inhibitor might disappear for further funding events. Similarly, personal funds invested was suggested by studies under the pecking order theory as a critical factor for obtaining external funding (Frid et al., 2015; Prasad et al., 2000). But our findings suggest that personal funds do influence on recurrent funding events. One possible suggestion for further research is that the personal funds invested operate as a signal for just the first funding received, as previous studies suggested, but not for additional funds obtained.

Several programs to help entrepreneurs obtain funding exist, but it will be useful as well to design policy tools to help entrepreneurs find a path of financing during the process of setting up a new company. More important than design programs to help with funding issues is to keep entrepreneurs in the financing system during their entrepreneurial gestational phase. This research has found that less affluent entrepreneurs are disadvantaged in that regard. Microloans programs have appeared in recent years for economic and socially disadvantaged entrepreneurs. However, this research indicates the necessity of going beyond these financial tools and assist financially less affluent entrepreneurs during the entire gestational phase.

The third paper utilized the theory of the Creative Class, a well-known and widely used approach that discusses the key driving factors for economic development regionally. This theory suggests that there is a social group, the Creative Class, that fosters innovation and entrepreneurship regionally. Thus, it enhances the life quality of those places, increasing the level of job creation and wealth. Since the scholarly community accepts the regional findings from theory in general, the theoretical innovation of the third research article is to apply this theory at the firm level to provide micro-fundamentals to the accepted macro-level findings.

At the methodological level, as the second paper did, this third article takes advantage of the time trends available in PSED. It also uses survival analysis and longitudinal modeling for analyzing new venture outcomes. The findings from this paper highlight that startups owned by more creative class members are strongly associated with job creation and firm survival. The results of this study suggest that policies can help entrepreneurs to transition from creative occupation to entrepreneurship. Similar to the previous research on entrepreneurial development at the regional level, the findings from this study challenge the standard measurement of human capital through educational attainment. Having more creative entrepreneurs on the team significantly explained three of the four performance outcomes investigated in this research. Thus, the previous working background is important for entrepreneurship, especially on entrepreneurial teams in which members help a creative occupation before starting a new company. Therefore, policies targeted to support people in creative professions to join and move towards entrepreneurship could benefit economic development, especially in less affluent areas.

Given the interdisciplinary nature of entrepreneurship research, the three research papers comprising this dissertation applied theories and methodologies coming from other disciplines. Applying them resulted in new findings for this research field and from them a new set of potential recommendations for the policy arena. As suggested by the findings in the first paper, the human capital theory should be investigated in detail before making policy recommendations for firms in the developing world, a result that has been found in previous research as well. Similar to what has been observed previously in other reward systems, the second paper sheds light on some factors that lead to the cumulative advantage that some entrepreneurs have in receiving external funding. The third research article revealed that the Creative Class theory, which regional scholars have found to impact regional-level entrepreneurship outcomes, helped in explaining firm-level performance as well. This dissertation, thus, emphasizes the importance of entrepreneurship scholars being aware of the advances in other research areas, both theoretically and methodologically, to ensure the continued advancement of this growing interdisciplinary field.

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APPENDICES

Appendix A

Inquiry of previous studies' dependent variable – Chapter 1

Paper	Independent variable/s	Independent variable Output / Input	Product	Process	Oragniz.	Marketing
Børing (2017)	Innovative enterprise, defined as product-innovative enterprises which introduced a product (i.e. a good or service) that is new or significantly improved with respect to its characteristics or intended uses during the period 2008–2010. This includes significant improvements in technical specifications, components, and materials, incorporated software, user friendliness or other functional characteristics. Process-innovative enterprises are enterprises which implemented a new or significantly improved method of production or delivery during the period 2008–2010.	Output	X			
Van Uden, Knoben, & Vermeulen (2016)	New or significantly improved products or services to the main market	Output	X			
Sung & Choi (2014)	New product development, product and service differentiation and number of patents	Output	X			
Smith, Collins, & Clark (2013)	Number of new products and services and knowledge creation capabilities	Output and input	X			
Nazarov & Akhmedjonov (2012)	Upgrading existing product line/service; Obtaining a new product-licensing agreement; Obtaining a new quality accreditation	Output	X			X
Goedhuys & Veugelers (2012)	if the firm successful introduced new technology that has substantially changed the way the main product is produced, in 1998–2002; if the firm successfully developed a major new product line in 1998–2002	Output	X	X		
De Winne & Sels (2010)	An index composed out of the weighted sum of four dichotomous variables representing achieved innovation projects, composed in this way: innovation of supporting processes (1) innovation of the production process (2), improvement of existing products/services (4) and development of new products/services (8) (weight of each variables between brackets).	Output and input	X	X		
Marotta, Mark, Blom, & Thorn (2007)	A firm is regarded as innovative from an input side if the sum of expenditure on innovation, in one expenses listed as new machinery; training in innovation and product testing, patents, licenses, introduction and commercialization of new products or R&D is larger than 0; A firm is regarded as innovative in terms of product if it has introduced at least one new technology for production, a product that is known to the market but new to the firm, a product that is new both to the market and to the firm	Output and input	X	X	X	

Shipton, West, Patterson, Birdi, & Dawson (2006)	Product innovation and in technical systems	Output and input	X	X		
Li, Zhao, & Liu, (2006)	Technological innovation in the firm. Measured through five variables on a 1-7 scale, composed by (1) Frequent introduction of new product ideas into production process; (2) high probability of success for new products being tested; (3) spending shorter periods in new product research and development; (4) radical improvement in the company's technology; and (5) frequently renewal of equipment.	Input				
Laursen & Foss (2003)	Firms' introduce a product or service innovation in the market.	Output	X			
Kyriakopoulos & de Ruyter (2004)	New product short-term financial performance refers and new product creativity	Output and input	X		X	
Kimberly & Evanisko (1981)	Technological innovation and administrative innovation	Output and input	X	X	X	

Appendix B

Available variables or those potentially created in the different UIS panel waves – Chapter one

	1998-2000	**2001-2003**	**2004-2006**	**2007-2009**	**2010-2012**	**2013-2015**
Age	YES	YES	YES	YES	YES	YES
Foreign capital	YES	YES	YES	YES	YES	YES
% Exports on sales	NO	YES	YES	YES	YES	YES
Make strategy (R&D investment p/employee)	YES	YES	YES	YES	YES	YES
Employment (log)	NO	YES	YES	YES	YES	YES
% Buy strategy (investment p/employee)	YES	YES	YES	YES	YES	YES
Cooperation and network agreements	NO	NO	YES	YES	YES	YES
% Professionals & technicians on workforce	NO	YES	YES	YES	YES	YES
HRM index (all variables)	NO	NO	YES	YES	YES	YES
% Employees trained	NO	YES	YES	YES	YES	YES

Appendix C

Public Policies to foster innovation trough human capital – Chapter one

Granted by	Objective	Targeted to PROFESSIONALS	Targeted to TRAINING	Targeted to HRM
National Agency for Research and Innovation (ANII)	Subsidy for internships in technology centers, foreign universities or companies, to acquire skills and knowledge to be applied in the company and facilitate access and transfer of knowledge and experience to improve the competitiveness of the company.	X		
Ministry of Industry, Energy, and Mining (MIEM)	Partial or total subsidy for projects of women entrepreneurs that promote innovation, generate substantial improvements in critical areas of their companies and have a positive impact on competitiveness. It is open to all entrepreneurs whose companies are SMEs and develop productive activities or services related to production, and which are also integrated into productive chains of ministerial interest. The projects must generate improvements in products, services, processes or commercialization, and the strengthening of the capacities and abilities of management of the company. The creation of quality employment aimed at young women will be positively valued.			X
National Agency for Research and Innovation (ANII)	Subsidy for the hiring of highly qualified professional staff, with the aim of implementing and developing research, development, and innovation processes in the company.	X		
National Agency for Research and Innovation (ANII)	Partial subsidy to hire a project formulator that works with the company towards the preparation of innovative proposals before the different instruments of the ANII. The formulator/s will be chosen by the company and must have a background to support their experience in the management and formulation of projects. The amount of the subsidy depends on the type of program that is being formulated.	X		
National Institute of Employment and Professional Training (INEFOP)	Subsidy for organizations or economic activities that identify training needs due to expansion factors, entry of new employees, new methods implementation or modification, work processes, updating technology, production, and marketing of new products and services, among others. The demand for training will be agreed between workers and employers. INEFOP will fund up to 100% of the training, assessing the contribution of the companies concerning the delivery of the courses during working hours, providing guidance and materials for its dictation.	X	X	
National Agency for Research and Innovation (ANII)	Partial subsidy for hiring abroad experts whose knowledge and skills are not in the country (the experts may be of Uruguayan or of foreign nationality), and aimed at solving specific problems of the company.	X		

National Agency for Research and Innovation (ANII)	Subsidy for the hiring of masters or doctorate students who carry out part of their studies and research in the company. It seeks to promote research and development activities within the business sector as well as the company academy linkages.	X		
National Agency for Research and Innovation (ANII)	Subsidy for funding masters or doctorate studies to professionals who are already working in the company. It seeks to promote research and development activities within the business sector as well as the company academy linkages	X		
National Agency for Research and Innovation (ANII)	The instrument supports the formation and consolidation of Sectoral Technological Networks that work in the business development of business, sectorial, or territorial competitiveness, synergistically combining the stakeholders' capacities and establishing new ones for the country. The stakeholders will be able to participate in these networks: technological centers, universities, and research institutes. Networks must achieve benefits for all the links that comprise it. Development plans will be financed that may include, among others, the following activities: Detection of technological bottlenecks for the productive sector. Search for solutions to them through the implementation of research and development projects. Technological transfer and absorptive activities, and diffusion of new technologies to the productive sector. The increase of qualified human resources. Establishment of basic communication and interaction capacities among the different key actors of the network. Investments to create or expand common technological services with impact on the productive sector.	X		
National Agency for Research and Innovation (ANII)	With resources coming from the ANII, activities that are directly related to the implementation of the project can be financed, among which the following can be mentioned. a) Fees for consultancies, technical assistance, and consultancies; b) For projects whose recognized amount does not exceed $ 3,200,000, the maximum recognizable amount for the company's personnel assigned to the project may not exceed $ 1,280,0004 c) Internships for master's and doctoral students. d) Expenses associated with visits and studies of the destination markets; e) Expenses related to commercialization and sales tests; f) Purchase of materials and supplies; g) Expenses in test equipment, tests, and laboratories; h) Expenses in facilities and/or labor and environmental protection measures; i) Purchase of bibliographic material; j) Software purchase and/or lease expenses; k) Expenses of technical and maintenance services associated with the projects; l) Intellectual property protection expenses m) Licensing costs and specific building adaptation for the installation of equipment; n) Unforeseen expenses of up to 5% of the project's financeable cost; and o) Expert fees for the formulation of projects to enhance Innovation for a maximum amount of ANII of $ 160,000.	X		

Appendix D

Hausman test, all models – Chapter one

	Firm product innovation	**Market product innovation**	**Implication**
Fixed effects, equation 1	Test: Ho: difference in coefficients not systematic chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 33.07 Prob>chi2 = 0.0009	Test: Ho: difference in coefficients not systematic chi2(12) = (b-B)'[(V_bV_B)^(-1)](b-B) = 60.12 Prob>chi2 = 0.0000	Fixed effects needed
Random effects, equation 1			
Fixed effects, equation 2	Test: Ho: difference in coefficients not systematic, chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B)=40.11 Prob>chi2 = 0.0002	Test: Ho: difference in coefficients not systematic chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 73.98 Prob>chi2 = 0.0000	Fixed effects needed
Random effects, equation 2			
Fixed effects, equation 3	Test: Ho: difference in coefficients not systematic chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 27.40 Prob>chi2 = 0.0170	Test: Ho: difference in coefficients not systematic chi2(14) = (b-B)'[(V_b-V_B)^(-1)](b-B) = 58.70 Prob>chi2 = 0.0000	Fixed effects needed
Random effects, equation 3			

Appendix E

Times between PSED interviews

database used for models 3 and 4– Chapter three

	Mean	Median	Max	Min
Months between wave 1 and 2	12.6	12.2	19	10
Months between wave 2 and 3	14.7	13.0	24	10
Months between wave 3 and 4	16.7	12.8	27	10
Months between wave 4 and 5	12.2	12.1	16	1
Months between wave 5 and 6	11.9	11.7	16	9.6

Appendix F

Descriptive statistics for each database used – Chapter four

Models I to III

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
CCE	0.0	0.0	0.0	0.5	1.0	7.0
CC%	0.0	0.0	0.0	26.0	50.0	100.0
EDUC	0.0	1.0	1.0	1.4	2.0	4.0
INDXP	0.0	2.0	10.0	20.1	30.0	298.0
STPXP	0.0	0.0	1.0	1.9	2.0	120.0
MEN	0.0	0.0	1.0	0.9	1.0	8.0
WHITE	0.0	1.0	1.0	1.3	2.0	10.0
AGE<24	0.0	0.0	0.0	0.1	0.0	4.0
AGE25-34	0.0	0.0	0.0	0.3	0.0	5.0
AGE35-44	0.0	0.0	0.0	0.3	0.0	5.0
AGE45-54	0.0	0.0	0.0	0.4	1.0	4.0
AGE>54	0.0	0.0	0.0	0.4	1.0	8.0
HNW	-1000000.0	25000.0	108000.0	802943.0	360000.0	153010000.0
TEAM	1.0	1.0	1.0	1.9	2.0	95.0
SWQ	0.0	150.0	660.0	2610.0	2500.0	81000.0
GRW	0.0	0.0	0.0	0.2	0.0	1.0
INNOV	0.0	0.0	1.0	0.8	1.0	3.0
BPLAN	0.0	0.0	0.0	0.8	2.0	3.0
FPRO	0.0	0.0	0.0	0.2	0.0	1.0
TOTFUND	0.0	0.0	1759.0	112716.0	14000.0	43450000.0
FUNPER	0.0	0.0	28.6	43.6	100.0	100.0
CONLAG	0.2	11.3	23.3	33.1	46.1	119.9

Models IV to VI

	Min.	*1st Qu.*	*Median*	*Mean*	*3rd Qu.*	*Max.*
CCE	0	0	0	0.52	1	6.00
CC%	0	0	0	24.95	50	100.00
EDUC	0	1	1	1.37	2	4.00
STPXP	0	0	1	1.72	2	32.00
MANG	0	10	32	30.53	49	83.00
WHITE	0	1	1	1.43	2	10.00
MALE	0	0	1	0.92	1	5.00
TEAM	1	1	1	1.84	2	15.00
HELPRES	0	0	1	1.52	2	8.00
PFUND(log)	0	0	0	1.34	0	13.06
INNOV	0	0	0	0.76	1	3.00
STYPE	0	0	0	0.46	0	5.00
QUIT	0	0	0	0.02	0	1.00

Models VII to IX

	Min.	*1stQu.*	*Median*	*Mean*	*3rdQu.*	*Max*
CCE	0.0	0.0	0.0	0.5	1.0	6.0
CC%	0.0	0.0	0.0	28.5	50.0	100.0
EDUC	0.0	1.0	1.0	1.4	2.0	4.0
STPXP	0.0	0.0	1.0	1.7	2.0	32.0
MANG	0.0	10.0	33.0	31.0	49.0	83.0
WHITE	0.0	1.0	1.0	1.4	2.0	10.0
MALE	0.0	0.0	1.0	0.9	1.0	7.0
TEAM	1.0	1.0	1.0	1.7	2.0	15.0
HELPRES	0.0	0.0	2.0	2.3	4.0	16.0
PFUND(log)	0.0	0.0	0.0	3.1	7.8	15.4
INNOV	0.0	0.0	1.0	0.8	1.0	3.0
STYPE	0.0	0.0	0.0	0.5	0.0	5.0

Models X to XII

	Min.	1stQu.	Median	Mean	3rdQu.	Max
CCE	0.0	0.0	0.0	0.5	1.0	6.0
CC%	0.0	0.0	0.0	26.8	50.0	100.0
EDUC	0.0	1.0	1.0	1.5	2.0	4.0
STPXP	0.0	0.0	1.0	2.0	2.0	120.0
MANG	0.0	6.0	26.0	27.7	47.0	82.0
WHITE	0.0	1.0	1.0	1.3	2.0	10.0
MALE	0.0	0.0	1.0	0.9	1.0	8.0
TEAM	1.0	1.0	1.0	1.8	2.0	55.0
HELPRES	0.0	0.0	1.0	1.6	3.0	8.0
PFUND	0.0	0.0	6.2	4.7	8.9	15.1
INNOV	0.0	0.0	1.0	0.8	1.0	3.0
STYPE	0.0	0.0	0.0	0.4	0.0	5.0
CONLAG	0.2	12.4	26.8	35.3	52.5	118.2