UNIVERSIDADE DE LISBOA

INSTITUTO SUPERIOR TÉCNICO

Essays on Workforce Demographics, Entrepreneurial Transitions and Startup Performance

Rui André Pereira Agostinho

Supervisor: Doctor Rui Miguel Loureiro Nobre Baptista

Co-Supervisors: Doctor Hugo Miguel Fragoso de Castro Silva

Doctor Stieneke Jolanda Annemarie Hessels

Thesis approved in public session to obtain the PhD Degree in Engineering and Public Policy

Jury final classification:

Pass with Distinction and Honour

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Jury

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Abstract

This dissertation presents three essays on how workforce demographics influence entrepreneurship and startup performance. The main dataset used is *Quadros de Pessoal,* a matched employer-employee dataset from Portugal.

Prior research shows that managers are more prone to become entrepreneurs. Studies also theorize a "rank effect," where older workers delay younger employees' promotions, reducing their likelihood of becoming managers, lowering their chances of entrepreneurial transitions. Another theory, the "small firm effect," argues that employees in small firms acquire broader skillsets, making them more likely to start businesses.

The first essay explores career paths leading into entrepreneurship. Using sequence analysis, we show that managers and small firm workers are more likely to become entrepreneurs. These workers often come from firms with younger managers and faster promotions to manager. Top managers are more likely than middle managers to transition to entrepreneurship.

The second essay examines how firms' workforce demographics influence entrepreneurship. Using discrete-time hazard models with entropy balancing, we highlight that workers in firms with older managers and slower promotions are less likely to become entrepreneurs. We observe that probabilities of entrepreneurial transitions are mediated through the likelihood of occupying managerial roles. Workers experiencing delayed progression are more likely to switch firms as wage employees, but not to become entrepreneurs. Again, top managers show higher entrepreneurial propensities than middle managers.

The third essay investigates how founders' and employees' backgrounds influence startup performance. We find that startups whose founders and employees stem from small firms, initially perform better. Over time, however, startups with founders and employees from large firms, especially those with managerial experience, perform better.

This dissertation highlights that managerial experience supports both entrepreneurial transitions and startup success, but that older workers delay younger employees' career progression, lowering entrepreneurial rates. Small firm experience benefits early performance but may hinder longer-term growth.

Keywords: entrepreneurship, firm demographics, managerial experience, firm size, startup performance

Resumo

Esta dissertação apresenta três ensaios sobre como as características demográficas da força de trabalho impactuam as taxas de empreendedorismo e o desempenho de *startups*. A base de dados usada nestes estudos é o Quadros de Pessoal, uma base de dados que liga empregadores e trabalhadores Portugueses.

Estudos anteriores mostram que gestores têm maior propensão para empreender. Outros estudos teorizam o chamado "*rank effect*", segundo o qual trabalhadores mais velhos atrasam a progressão dos mais jovens, reduzindo a sua probabilidade de alcançarem cargos de gestão, e, consequentemente, de empreenderem. Outra teoria, o "*small firm effect*", defende que trabalhadores em pequenas empresas adquirem competências diversificadas, tornando-se mais propensos a empreender.

O primeiro ensaio analisa percursos profissionais que conduzem ao empreendedorismo. Usando *sequence analysis*, mostramos que gestores e trabalhadores de pequenas empresas têm maior probabilidade de empreender. Estes trabalhadores tendem a trabalhar em empresas com gestores mais jovens e promoções mais céleres. Gestores de topo são mais propensos a criar empresas do que gestores intermédios.

O segundo ensaio investiga de que forma a demografia das firmas influencia as taxas de empreendedorismo. Utilizando modelos de risco discreto com *entropy balancing*, mostramos que trabalhadores em empresas com gestores mais velhos, e com promoções tardias, têm menor probabilidade de empreender. Este efeito é mediado pela ocupação de cargos de gestão. Trabalhadores com progressão lenta mudam mais frequentemente de empresa, mas não empreendem mais. Novamente, gestores de topo mostram maior propensão empreendedora do que gestores intermédios.

O terceiro ensaio analisa o impacto das experiências anteriores de fundadores e trabalhadores no desempenho de *startups*. Mostramos que *startups* cujos fundadores e trabalhadores têm experiência em pequenas empresas, obtêm melhor desempenho inicial, mas que, ao longo do tempo, aquelas cujos fundadores e trabalhadores são oriundos de grandes empresas, sobretudo com experiência de gestão, obtêm melhores resultados.

Esta dissertação sublinha que experiência de gestão apoia tanta a probabilidade de empreender como o sucesso de *startups*, mas que trabalhadores mais velhos atrasam a progressão na carreira dos mais novos, diminuindo as suas chances de empreender. Experiência em pequenas empresas beneficia o desempenho inicial, mas pode prejudicar o crescimento a longo prazo.

Palavras-chave: empreendedorismo, demografia de empresas, experiência de gestão, tamanho de empresas, performance de *startups*

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E viva o RED e a Manteiga de Alho!

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List of Acronyms

QP: Quadros de Pessoal

SCIE: Sistema de Contas Integradas de Empresas

LP: Labour Productivity

FS: Firm Size

Chapter 1

Introduction

An aging population is often linked with declining entrepreneurship rates (Lévesque & Minniti, 2006; Liang et al., 2018). As people age, aspects that are relevant for entrepreneurship, such as creativity and risk-taking, decline, making workers less likely to transition to entrepreneurship. Since entrepreneurship plays a key role in economic development (e.g., Baumol & Strom, 2007; Thurik et al., 2013), any effects that lead to a decrease in entrepreneurial propensity in a society may slow its subsequent economic progress, making this area a core path for entrepreneurial research.

An aging society may also make it harder for workers to progress up the career ladder, and reach managerial ranks (Bianchi et al, 2021). This may be worrying, since accumulating managerial experience constitutes an important route towards entrepreneurship. By working as managers, employees develop skills such as strategy formulation, opportunity recognition and evaluation, resource building and accumulation, or coordination and supervision of workers (Helfat & Martin, 2015). All of these are crucial to perform managerial tasks but are also valuable skills for entrepreneurs. As such, if workers are barred from acquiring managerial skills, entrepreneurship rates could decline (Lévesque & Minniti, 2006).

The "rank effect theory" proposed by Liang et al. (2018) links population aging with decreasing entrepreneurship rates. According to the authors, workers tend to enter firms at lower levels and then progress towards managerial positions. However, when a country has an aging workforce, managerial positions tend to be occupied by older workers. Older employees are less likely to become entrepreneurs, and due to their higher wages, are also less likely to switch to other firms (Troske, 1999). As such, the presence of older managers in firms will tend to slow down the career progression of younger workers into managerial ranks. Since managerial experience allows workers to develop skills that are useful for entrepreneurship, the lack of such experience would result in lower entrepreneurship rates across the age spectrum. When such an effect takes place, even younger, potentially more innovative and less risk-averse individuals may be kept away from entrepreneurship because they mainly build up firm-specific skills in non-managerial roles, lacking managerial skills. Liang et al. (2018) show that countries with older workforces have lower entrepreneurship rates than those with younger workforces, finding evidence for their theory, at the country-level.

The size of the firms where employees work has also been shown to impact their likelihood of becoming entrepreneurs. In fact, past research has stated that a disproportionate number of entrepreneurs stem from small firms, in a theory coined the "small firm effect" (Elfenbain et al., 2010; Parker et al., 2009). Several reasons have been put forth to explain this finding. Parker et al. (2009) indicate that small firms have less rigidly defined job hierarchies, allowing their workers to perform more diverse tasks than workers in larger firms. This allows for the development of a wider skillset, increasing the likelihood of becoming an entrepreneur. Dobrev and Barnett (2005) show that smaller firms ease the creation of broad outside networks, which can facilitate future entrepreneurial transitions. On the other hand, Kacperczyk and Marx (2016) propose a different explanation behind the small firm effect. The authors indicate that smaller firms provide workers with fewer opportunities for promotions, which could lead some of their employees who are looking for further career development to create their own firms. This statement could be viewed as a push factor leading workers into entrepreneurship, as the transition would happen not necessarily due to an accumulation of relevant skills, but rather due to frustration when faced with impeded job progression.

Moreover, the performance of startups (and not just the likelihood of entrepreneurial transitions), is also affected by both the managerial experience and prior firm size of their founders. Managers develop a broad set of technical and non-technical skills, which provides a well-rounded understanding of multiple business functions, enhancing startup performance (Lazear, 2005). Similarly, workers in smaller firms are involved in a wide range of tasks, developing a diverse skillset and entrepreneurial mindset, which may lead to better performing startups (Shane, 2003; Elfenbain et al., 2010).

The three essays in this dissertation examine how the characteristics of Portuguese firms and of their workforces influence entrepreneurship, with a particular focus on the roles of worker age, managerial experience, and firm size. The main data used in all three essays comes from *Quadros de Pessoal*, a Portuguese matched employer-employee dataset, with extensive information at both the firm and worker level.

In Chapter 2, we analyse what career paths are more likely to lead workers to become entrepreneurs. We use sequence analysis to follow the career paths of workers starting a new job spell, following them over a 10-year period. By doing so, we are able to observe workers through four possible career stages - business ownership, manager employees, non-manager employees, and non-employment. Sequence analysis allows us to understand what career paths are more likely to lead to entrepreneurial transitions, via the analysis of clusters of individuals with similar career paths. We confirm that occupying managerial positions is a common pathway to become an entrepreneur. Moreover, we show that workers who occupy managerial positions, compared to those in non-managerial ones, work in firms with younger managers, and where workers are promoted to managerial ranks at a younger age. These findings go in accordance with the rank effect, as proposed by Liang et al. (2018): by working in firms with such characteristics, these workers may not have faced delayed career progressions, leading to the accumulation of managerial experience at younger ages, which could explain their higher propensity to become entrepreneurs. We also find that managers work in smaller firms than non-managers, which is in line with the small firm effect. Moreover, we find evidence that top managers appear more likely than middle managers to become entrepreneurs. However, sequence analysis, despite being a powerful descriptive tool, does not allow us to make inferences regarding causality. Therefore, our results in Chapter 2 work as a strong incentive to the tests performed in the studies shown in Chapters 3 and 4.

Chapter 3 draws from our findings shown in Chapter 2, which indicate that workers in firms with younger managers and with lower ages at managerial promotion have a higher propensity for entrepreneurial transitions. In this essay, we test if the rank effect is observable within the Portuguese workforce, examining how the age characteristics of firms' workforces affect the likelihood of workers occupying managerial positions, and, in turn, how this affects the likelihood of workers transitioning to entrepreneurship. To our knowledge, no other studies have analysed the rank effect by looking directly at how firms' managers may be delaying younger workers' accumulation of managerial skills, and how this may affect entrepreneurial rates. Our analyses complement the ones conducted by Liang et al. (2018), going further than what the authors did in their study. First, we test if the demographic characteristics of the workforce may lead workers to occupy managerial ranks at later ages. Liang et al. (2018) theorize this, but never test it. Furthermore, we also explicitly include the characteristics of the managerial workforce in our models, since, according to the rank effect theory, managers are the ones that more directly will be delaying the career progression of younger, less-experienced workers into managerial ranks (once more, Liang et al. (2018) propose this, but do not test it). We also separately look into middle and top managers, to try to understand if workers at each of these levels will impact the rank effect differently. Lastly, we examine if there is a push-factor leading workers into entrepreneurship, testing if workers facing delayed career progressions will be more likely to become entrepreneurs. Using discrete-time hazard models, our findings suggest that working in firms with older middle and top managers lowers the likelihood of workers occupying managerial ranks, which in turn lowers their likelihood of becoming entrepreneurs. We also show that workers that face limited promotion options within firms are more likely to move to other firms as paid employees, but not to transition to entrepreneurship. Lastly, we highlight that top managers are more likely to become entrepreneurs than middle managers, but less likely than middle managers to move to other firms as paid employees. These findings suggest that the rank effect is observable in our sample.

In Chapter 4, we build on the findings displayed in Chapter 2 that suggest that employees who, during their careers, work in smaller firms, are more likely to end up becoming entrepreneurs. However, in Chapter 4, instead of analysing what variables impact entrepreneurial transitions, we focus on what characteristics of startups' founders and employees will affect startup performance. Specifically, we are informed by two branches of entrepreneurship research: first, the one that posits managerial experience as a predictor of entrepreneurial success (Bosma et al., 2004; Dobrev & Barnett, 2005); second, from the small firm effect, which states that employees from smaller firms are more likely (and more apt) to transition to entrepreneurship (Parker, 2009; Elfenbein et al., 2010). We investigate if startups whose founders have managerial experience outperform those created by entrepreneurs without it. Additionally, we examine if founders who previously worked at small firms create more successful startups when compared to those who worked at larger firms. Moreover, we analyse if past firm size and managerial experience of startup employees, rather than just that of their founders, will have an impact on performance. Lastly, we test if these characteristics of a startup's founders and employees have different impacts on performance, dependent on the startup's age. There are few prior studies analysing how startup's employees may affect performance, and, to the best of our knowledge, none who have studied if their past managerial experience and the size of their prior firms have an impact on this relationship. Our findings suggest that, in the early stages, startups founded by individuals from smaller firms outperform those founded by individuals with experience in larger firms. Similarly, startups that initially hire more employees coming from small firms tend to perform better than those whose hirees come from larger firms. However, in the later years of a startup's life, we find that the pattern reverses: startups founded by individuals with experience in larger firms, especially those with prior managerial experience, outperform those whose founders came from smaller firms. Likewise, we highlight that hiring employees with managerial experience from larger firms becomes a predictor of better performance in a startup's later stages.

We are confident that the results from all three essays are both econometrically robust and economically meaningful. Our findings indicate that managerial experience is a predictor of entrepreneurial transitions. We also show that the better performing startups, after the initial years of uncertainty, are those founded by individuals who had been managers in large firms. However, we find that the presence of older managers within firms delays the accumulation of managerial experience by younger workers, who, when faced with such impediments, are then less likely to become entrepreneurs of possibly high-performing firms. Such evidence should be taken into account by both decision-makers and academic researchers, since this barring of skill acquisition could lead to lower entrepreneurial rates amongst the most apt, possibly impeding further economic growth and development.

Chapter 2

What Career Paths Lead to Entrepreneurial Transitions? A Career Description via Sequence Analysis

2.1. Introduction

Different career pathways may lead individuals to become entrepreneurs (Burton et al., 2016). In fact, most entrepreneurs spend several years working as paid employees prior to opening their own firms (Gendron-Carrier, 2025). Importantly, gaining experience working in managerial positions possibly constitutes an important route towards entrepreneurship. As young workers enter firms, progress up the career ladder and reach managerial positions, they acquire financial capital and networks of contacts, but also skills based on knowledge and experience that translate into dynamic capabilities (Eisenman & Bower, 2000). Arguably, such capabilities should translate to entrepreneurship, since they would also be of great importance in such a context. Therefore, one would expect that workers who have acquired managerial experience are more likely to transition to entrepreneurship.

It also seems reasonable to argue that those who acquire managerial experience and skills earlier in their careers are more likely to become entrepreneurs than those who do so later. Qualities like creativity and risk-taking which are relevant for entrepreneurship usually decline with age. Lévesque and Minniti (2006) indicate that an aging workforce should lead to a decline in entrepreneurship, especially among young workers.

Liang et al. (2018) offer a theory linking managerial experience to entrepreneurship by proposing that there exists a “rank effect” through which workforce aging causes declining entrepreneurship rates. According to Liang et al. (2018), in societies with aging workforces, managerial positions tend to be occupied by older workers, slowing down the career progression of younger ones. Thus, in societies with older workforces (and, in particular, with older managers) younger workers are only able to gain managerial experience later in their lives, when compared with people in firms with younger workforces. Since experience in managerial roles allows workers to develop capabilities that are useful for entrepreneurship, the lack of such experience results in lower entrepreneurship rates across the age spectrum.

Previous research also highlights that small firms disproportionately produce future entrepreneurs, in a theory coined the small firm effect. Employees in small firms are often required to take on a large variety of tasks, as these workplaces typically lack rigid hierarchical structures. Consequently, these employees may end up developing broad skillsets, and, similarly to what happens to employees with managerial experience, this could ease their transitions to entrepreneurship.

In this study we analyse how different career paths may lead workers into entrepreneurship. Namely, we are interested in understanding if workers who occupy managerial positions throughout their careers are more likely to become entrepreneurs. We examine if the demographic characteristics of the firms in which they work during their careers – particularly the age of the firm's workforce (and specifically of the managers), and the firm's size - impact their likelihood of entrepreneurial transition. To address this, we use sequence analysis (Abbot, 1995) to develop a descriptive examination of career paths leading to entrepreneurship. Sequence analysis allows us to study transitions to intermediate career states that typically would not be observed if we were just looking at the transition-to-entrepreneurship event. We are concerned with what types of labor market experiences, namely employment as manager, employment as a non-manager employee, and non-employment, precede entrepreneurship, and what kinds of individuals (in terms of age, formal education and skills) follow different trajectories.

This study makes an original contribution by taking a career-based approach to examine the roles of managerial experience and firm characteristics in shaping transitions to entrepreneurship. By doing so, we are able to understand if different career paths are more likely to spawn business owners, and to understand if the predictions of the rank effect and of the small firm effect are observable in our sample.

We make use of *Quadros de Pessoal*, a longitudinal matched employer-employee database covering the Portuguese economy that provides detailed information at both the worker-level and at the firm-level. We focus on individuals starting a new job spell as wage workers between 2005 and 2009, following their careers for a ten-year period.

We confirm that reaching managerial positions is a common pathway towards becoming an entrepreneur, as predicted in past literature. We also find, in line with the small firm effect, that workers in smaller firms are more likely to transition to entrepreneurship. Moreover, our findings suggest that firms with younger managers, and in which managerial promotions happen at younger ages, generate more entrepreneurs, which goes in accordance with the rank effect. Lastly, separating between top and middle managers, our findings suggest that the former are more likely to become entrepreneurs.

2.2. Background

Prior research on entrepreneurship has sought to identify the factors that make certain workers more likely to transition into entrepreneurship than others. Previous studies have examined the role of prior work experience, demographic attributes of the workforce, and firm-specific characteristics that may shape entrepreneurial propensity.

Regarding past work experience, past literature highlights that experience acquired while being employed as a wage worker in firms can play a significant role in fostering the success of entrepreneurs (Franco, 2005). In particular, managerial experience can help employees build up skills that are relevant to entrepreneurship (Kim et al., 2006). Past research suggest that working as a manager can lead to the accumulation of skills required to develop innovative business opportunities (Oberschachtsiek, 2012), and that it allows workers to have access to organizing and supervising skills (Baptista et al., 2012). Managerial tasks involve coordinating teams, setting objectives and deadlines, and rewarding performance, as well as handling conflict between subordinates (Burgoyne & Stuart, 1976). Through these activities, managers acquire knowledge about multiple functions within the firm (rather than sticking to knowledge that is specialized in a single function) and build up leadership skills. None of this knowledge is easily accessible to non-managerial employees, providing an important advantage to managerial workers.

Crucially, while the aforementioned skills are important for managers, they are also predictors of future entrepreneurial success (Stuetzer et al., 2013). These skills, often called dynamic capabilities (Heaton & Teece, 2013), are central to entrepreneurial success, as they determine if firms are able to identify opportunities and implement strategies that could lead to profitable investments. This positive link between managerial experience and entrepreneurial propensity could then be explained by the fact that access to these capabilities is more directly available to managers than to non-managers (Eisenman & Bower, 2000).

Moreover, while past research has often analysed managers as an homogeneous group, it is possible that top and middle managers would have different likelihoods of venturing into entrepreneurship, as the tasks they perform and skillsets they develop are not the same. Top managers have more external-oriented responsibilities, having to make strategic decisions that may have great impact on a company's performance, by leading its innovation processes and goals via market and technology monitoring (Mintzberg, 1983). On the other hand, middle managers have more internal-oriented responsibilities, being more directly involved in day-to-day operations, being responsible for managing teams and making sure communication between lower-level workers and top management flows smoothly (Floyd & Wooldridge, 1997). Although both types of experience obtained would be useful for entrepreneurs, it is possible that top managers, who have more contact with external decision-makers, having broad networks of professional contacts, would find it easier to spot entrepreneurial opportunities than middle managers, making them more likely to become entrepreneurs.

When it comes to age characteristics of the workforce, prior research suggests that while some characteristics conducive to entrepreneurship improve with age, others decline with it. Younger individuals tend to be more creative in their thinking (Azoulay et al., 2020), may be better at identifying entrepreneurial opportunities due to greater cognitive and physical abilities (Gielnik et al., 2012), and are generally less risk-averse (Miller, 1984). Additionally, because launching a new firm entails substantial sunk costs, the period available for recovering these costs is shorter when the expected lifespan of the entrepreneur is limited. As a result, younger individuals may find it more advantageous to start businesses with high sunk costs, as they have a longer time horizon ahead (Wagner, 2005). Conversely, older individuals have had more time to accumulate human capital, making them more experienced and better equipped to assess business opportunities (Lafontaine & Shaw, 2016). They are also more likely to have amassed financial capital, providing them with greater access to the resources necessary to start a firm (Blanchflower & Oswald, 1998).

One theory that links demographic characteristics of the workforce, managerial experience and likelihood of entrepreneurial transitions was proposed by Liang et al. (2018). The authors argue that the inflow of entrepreneurs will be hampered by an aging workforce. With an aging workforce, older workers are likely to occupy the key managerial positions that provide relevant experience for entrepreneurship, delaying the promotions of younger employees into managerial roles, and, in turn, delaying the accumulation of such experience. As a consequence, entrepreneurship rates will decline. Liang et al. (2018) dub this mechanism the "rank effect": An individual's rank in the firm determines their opportunities to accumulate human capital that is required to start a business. When individuals obtain a managerial rank within an organization, they have a higher chance to obtain useful experience for starting a business. If this opportunity is not provided, the expected return from becoming an entrepreneur is lower, so employee entrepreneurship, on average, declines.

Lastly, another key determinant of entrepreneurial transitions is the size of the firms where entrepreneurs were previously employed. Prior research, building on the "small firm effect" theory, has found that a disproportionate number of startups are founded by individuals with experience in smaller firms (Parker, 2009; Elfenbein et al., 2010).

Several explanations have been proposed for the small firm effect. One argument suggests that the less formalized hierarchies in small firms provide workers with greater autonomy, exposing them to a broader range of tasks and enabling them to develop more diverse skillsets (Parker, 2009). Another perspective posits that employees in small firms acquire broader external networks, which can later facilitate entrepreneurial transitions by providing access to valuable information on potential business opportunities (Dobrev & Barnett, 2005). Additionally, it has been suggested that small firms tend to attract individuals who are less risk-averse, making them more likely to pursue entrepreneurship later in their careers (Parker, 2005). Finally, because small firms often offer less stable employment and lower wages than larger firms, their employees face lower opportunity costs when leaving their positions, easing their transition to entrepreneurship (Troske, 1999).

2.3. Methodology and Sample Construction

We use sequence analysis to examine the workers' career patterns that lead to entrepreneurship. A career pattern refers to the "number, duration, and sequence of jobs in the work history of individuals" (Savickas, 2001: 54).

Sequence analysis is a method originally stemming from natural sciences (Abbot & Forrest, 1986). Sequence analysis detects similar patterns in sequences of states. In the case of careers, a sequence is a chronologically ordered set of labor market states through which an individual goes over a relatively large time frame, and which may include many spells of consecutive states. This methodology has been used to identify career patterns linked to self-employment and entrepreneurship by Koch et al. (2021) and Backman et al. (2021).

The first step in sequence analysis is to compute distances (or dissimilarity) scores for each pair of sequences. We do this by using an optimal matching algorithm (MacIndoe & Abbott, 2004; Rowe, 2017). This algorithm measures the distance between sequences of different lengths, by calculating how many edits or steps are needed to transform one sequence into the other. This pairwise distance measures the cost of making both sequences equal through substitution, insertion or deletion of states. The optimal matching algorithm determines the cheapest solution corresponding to the minimum distance between each pair of sequences. In our case, the cost of substituting one state for another within a sequence comes from the observed rates of transitions across states, meaning that transitions that occur more often have a lower cost of substitution. The insert and deletion costs are left at a default value of 1 (Halpin, 2017; Backman et al., 2021). To perform sequence analysis, we used the SADI package, from Stata (Halpin, 2017).

After the sequence analysis, we perform a cluster analysis, based on the distance matrix for all pairs of sequences that result from the optimal matching algorithm. Cluster analysis produces groups of similar sequences and can be used to describe families of sequences, thus reducing the complexity of analyzing individual sequences. The clustering of similar sequences is done through the 'partitioning around medoids' algorithm. Kaufman and Rousseeuw (1990) propose that this method is more robust than the conventionally used k-means approach. The optimal number of clusters was calculated using the Caliński-Harabasz cluster stopping-rule (Caliński, & Harabasz, 1972; Halpin, 2017).

For our analyses, we use *Quadros de Pessoal* (QP), a Portuguese matched employer-employee longitudinal dataset, rich in detailed information both at the worker- and at the firm-level. The dataset originates from administrative data collected for the Portuguese Ministry of Employment and Social Security through a mandatory yearly survey.

The original dataset accounts for over 2 million workers in more than 300 thousand distinct firms per year. At the worker-level we have data on age, tenure, education, gender, wages, occupation and a variable for hierarchical position which allows us to identify workers in managerial positions. At the firm-level, we have information on age, number of employees, industrial sector and geographical location. *Quadros de Pessoal* has been extensively used in researching new firm creation and entrepreneurship including, for example Geroski et al. (2010) and Ribeiro et al., (2022).

We focus on cohorts of labor market entrants joining the labor market between 2005 and 2009, and follow them for a period of ten years. A variable distinguishes between paid-employees and business owners. Similarly to other studies using the same dataset (e.g., Kallmuenzer et al., 2021; Ribeiro et al., 2022), we define entrepreneurs as workers who are identified as business owners of a firm.

Our sequence analysis includes four states that each worker may be in at a given moment: entrepreneur, manager, non-manager employee, and non-employment.[1] As we are concerned about describing paths to entrepreneurship, we consider only individuals who eventually transition to entrepreneurship while in our sample. In addition, because our sample looks at new job spells, all sequences begin with an employment state (either manager or non-manager employees). Thus, in our analysis, a sequence will describe the chronological organization of these four states over the ten-year period after appearing in the sample described above. In the end, our sequence analysis sub-sample is composed of 6407 individuals that eventually are entrepreneurs in the ten-year period.

2.4. Results

In this section we present the results obtained via sequence analysis. As described earlier, sequence analysis computes a pair-wise measure of similarity between the sequences of all individuals in our sample. Then, through cluster analysis, similar sequences are grouped together. As there can be as many distinct sequences as there are individuals, clustering allows for a more general discussion by identifying similar trajectories. For all cases, the optimal number of clusters was calculated using the Caliński-Harabasz cluster stopping-rule (Caliński, & Harabasz, 1972; Halpin, 2017).

Figure 2.1 displays the chronogram of sequences in four clusters. The chronogram represents the proportional distribution of individuals across four labour market states (business owner, manager, non-manager, non-employment) over time, for each cluster. The vertical axis gauges the proportion of individuals in each of the four states for each moment in time, which is measured on the horizontal axis. We should point out that the clusters are not all the same size, with the cluster named Managers (top-right corner) being the smallest, including only about 13% of the individuals in the analysis. The other three clusters are more balanced in size.[2]

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[1] *Quadros de Pessoal* does not include information on the unemployed. We classify an individual as being non-employed in a given year if they are not observed in the dataset in that year. Individuals may be out of the data set because they are unemployed or inactive, or they have moved to a sector of the economy not covered by the survey, in particular public administration. Given that moves from the private to the public sector are relatively rare in Portugal, most individuals classified as non-employed will either be unemployed or inactive.

[2] See Figure 2.A.1 in Appendix 2.A for the chronograms shown in Figure 2.1, with the absolute number of individuals per cluster.

The chronograms reveal two dominant trajectories leading to long-term entrepreneurship: The cluster presented in bottom-right corner is largely composed of individuals who soon after starting a spell working for others (as managers or subordinates) quickly leave their jobs and become business owners (which we call Fast Transitioners). Individuals in this cluster may have identified an opportunity before and were always determined to start their own venture, placing little relevance to whichever experience they could amass working for others. The top-left cluster is largely dominated by people moving into non-employment after relatively short periods as paid employees. They then find an alternative occupational choice in entrepreneurship (this is why we refer to them as Necessity). The bottom-left cluster is composed of workers mostly starting as non-managerial employees (Non-Managers), and in the top-right cluster we have those starting as managers (Managers).

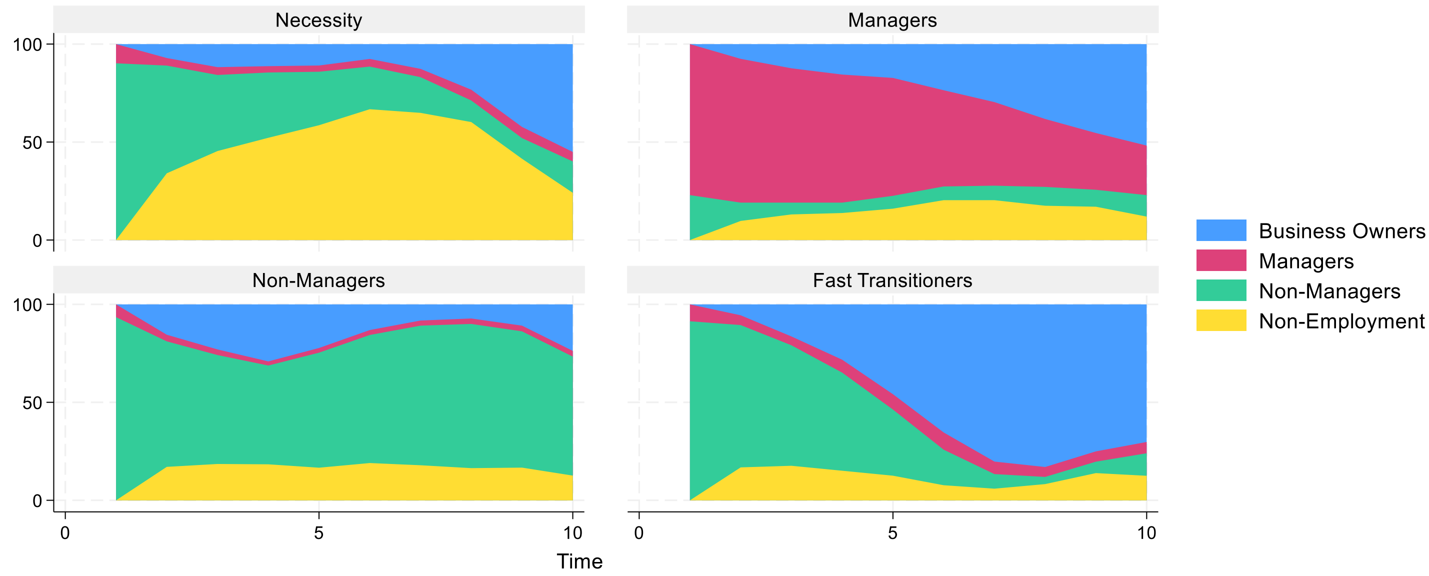

Figure 2.1 - Sequence analysis proportional distribution chronograms by cluster.

Given that we are especially concerned with the role of managerial experience in transitions to entrepreneurship, we mainly focus on contrasting the Managers and Non-Managers clusters. These are individuals who accumulate some experience working for others before transitioning to entrepreneurship. The chronograms show that workers in the Managers cluster transition earlier and more prominently into entrepreneurship than those in the Non-Managers cluster. As argued in our background section, time spent in managerial positions may facilitate transitions into entrepreneurship, since managers acquire specific capabilities that are valuable in entrepreneurial ventures, such as those required for successful opportunity discovery and exploitation, as well as for coordination and supervision of tasks across different functions.

We complement this chronogram analysis with a further description of the clusters of career pathways by looking at a set of summary statistics when individuals enter our sample (Table 2.1).[3] By looking at the moment they enter our sample, we can describe these individuals before they can potentially transition to entrepreneurship. Analyzing Table 2.1, we can see that those in the Managers cluster display characteristics that are significantly different from the other clusters, and particularly different from the Non-Managers cluster. In the Managers cluster, individuals are slightly older, much more educated, and more highly skilled[4] (as expected, given that in this cluster, most individuals are initially top or middle managers). These differences may help explain the more rapid transitions into entrepreneurship compared to the Non-Managers cluster, as these are individual traits often conducive to entrepreneurship.

In addition, we find that people in the Managers cluster join firms with older workforces (statistically significant at least at the 5% level in a one-sided test), but with younger managers (both younger top and middle managers). All differences are statistically significant at least at the 5% level in a one-sided test), when compared with the Non-Managers cluster. Importantly, the firms that individuals in the Managers cluster join also promote to managerial positions earlier than in the Non-Managers cluster (statistically significant at least at the 5% level in a one-sided test). These differences relative to the age variables at the firm level are suggestive of the rank effect, providing support for Liang et al's. (2018) theory.

Finally, Managers are also initially in firms with higher knowledge intensity, and with fewer employees. Since those in the Managers cluster seem more likely to transition to entrepreneurship than those in the Non-Managers cluster, the fact that the Managers come from smaller firms goes in accordance with the "small-firm effect" (Sørensen, 2007; Elfenbein et al., 2010).

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[3] Table 2.1 reports average values computed only for the first observation of each individual in the sequence analysis sample, within each cluster. We choose to present only statistics at the first year rather than the full sequence analysis period not only to describe pre-entrepreneurship characteristics, but also because firm level variables such as the age of managers/workforce or age when reaching managerial roles, firm size/age, technology/knowledge intensity or even high skill occupations are meaningless for those in the non-employment state.

[4] The variables identifying the skill levels, follow the ISCO-08 classification. The level "high skills" corresponds to the Managers, Senior Officials, and Legislators and the Professionals ISCO-08 major groups. Workers in these occupations perform tasks that involve high-level problem solving and decision making requiring advanced and specialized knowledge.

Table 2.1 - Descriptive statistics of clusters obtained via sequence analysis, calculated at sample entry.

	Cluster				
	Necessity	Managers	Non-Managers	Fast Transitioners	All
Age	27.42	29.63	27.18	28.04	27.78
	(5.77)	(4.95)	(5.69)	(5.57)	(5.65)
Higher education	0.19	0.64	0.11	0.21	0.23
	(0.39)	(0.48)	(0.31)	(0.41)	(0.42)
Wage (euros)	709.98	1367.42	681.15	810.32	809.71
	(576.10)	(1215.91)	(402.29)	(2160.28)	(1243.24)
Low skills	0.09	0.00	0.10	0.07	0.08
	(0.29)	(0.07)	(0.30)	(0.25)	(0.27)
Medium-low skills	0.65	0.16	0.70	0.68	0.61
	(0.48)	(0.37)	(0.46)	(0.47)	(0.49)
Medium-high skills	0.15	0.20	0.12	0.15	0.15
	(0.36)	(0.40)	(0.32)	(0.36)	(0.35)
High skills	0.11	0.63	0.08	0.10	0.17
	(0.31)	(0.48)	(0.27)	(0.30)	(0.37)
Firm age	13.10	12.74	11.06	11.48	12.07
	(29.51)	(23.69)	(14.00)	(22.07)	(23.30)
Firm size (number of employees)	554.09	261.90	440.28	294.72	420.29
	(2213.80)	(1489.85)	(1884.64)	(1474.98)	(1874.00)
Sales (millions of euros)	54.26	31.55	34.41	25.86	38.66
	(312.04)	(221.53)	(213.79)	(200.55)	(249.76)
High-tech manufacturing	0.03	0.03	0.05	0.04	0.04
	(0.17)	(0.16)	(0.21)	(0.20)	(0.19)
Low-tech manufacturing	0.09	0.07	0.10	0.11	0.10
	(0.29)	(0.25)	(0.30)	(0.31)	(0.29)
Knowledge-intensive services	0.37	0.53	0.32	0.36	0.38
	(0.48)	(0.50)	(0.47)	(0.48)	(0.48)
Less knowledge-intensive services	0.41	0.29	0.43	0.39	0.40
	(0.49)	(0.46)	(0.49)	(0.49)	(0.49)
Other sectors	0.09	0.09	0.10	0.09	0.10
	(0.29)	(0.28)	(0.30)	(0.29)	(0.29)
Median age of firm’s workforce	33.53	34.75	33.83	33.92	33.87
	(6.14)	(6.37)	(6.42)	(6.13)	(6.26)
Median age of firm’s managers	38.58	35.40	39.16	38.78	38.27
	(8.16)	(7.18)	(8.81)	(8.72)	(8.43)
Median age of firm’s top managers	37.29	35.02	39.02	36.88	37.26
	(8.35)	(7.46)	(9.41)	(9.14)	(8.77)
Median age of firm’s middle managers	39.46	36.53	39.41	39.57	38.98
	(8.41)	(8.09)	(8.68)	(8.78)	(8.58)
Firm’s median age at promotion to managerial roles	33.28	32.22	33.79	34.02	33.40
	(5.39)	(5.34)	(5.99)	(6.45)	(5.81)
Observations	2,169	811	1,845	1,582	6,407

Notes: Statistics computed at labor market entry.

We delve further into the different entrepreneurial propensities of employees of different sized firms, by running another sequence analysis model, this time separating workers into five labour market states (business owner, employee of small firm, employee of medium-sized firm, employee of large firm, non-employment)[5]. Figure 2.2 displays the chronogram of sequences in six clusters, displaying the proportion of individuals in the y-axis.[6]

[5] We consider small firms as having five or less workers, medium-sized firms as having between six and 49 workers, and large firms as having 50 or more workers.

[6] See Figure 2.A.2 in Appendix 2.A for the chronograms shown in Figure 2.2, with the absolute number of individuals per cluster.

We once again have a cluster composed of workers who quickly transition into entrepreneurship after short periods as paid employees (that we once more call Fast Transitioners). Two clusters are composed of workers who spend a significant amount of time in non-employment: in the cluster we call Necessity 1, these workers spend some years working in large firms or being in non-employment, before transitioning to entrepreneurship; Necessity 2 is more pronounced, in which an even larger share of workers spend a longer period of time in non-employment. Lastly, we have three clusters in which the workers who compose them, prior to transitioning to entrepreneurship, spend time working in small firms, in medium-sized firms or in larger firms, respectively, as per the names we give each cluster. As we can see, the workers in the Small Firm Workers cluster transition earlier into entrepreneurship than workers in the two other clusters. This finding goes once more in accordance with the small firm effect.

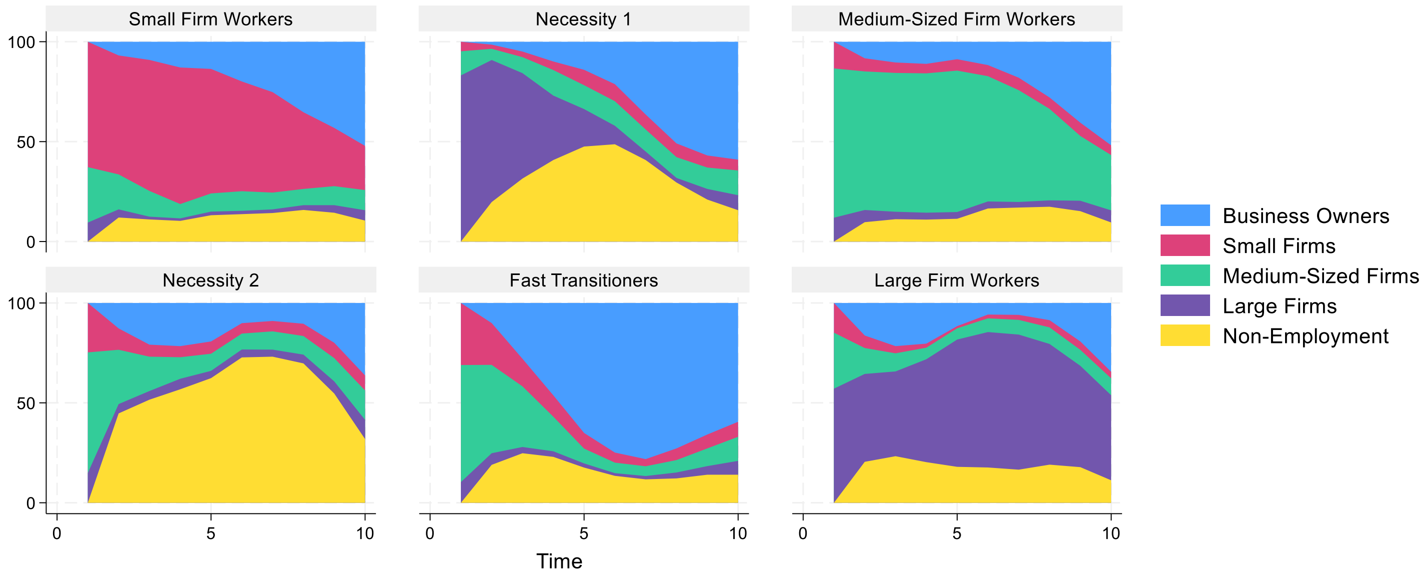

Figure 2.2 - Sequence analysis proportional distribution chronograms by cluster, separating by firm size.

We provide a further description of the clusters by looking at summary statistics when individuals enter our sample, as shown in Table 2.2. Comparing the workers in the clusters Small Firm Workers, Medium-Sized Firm Workers and Large Firm Workers, we can see that those in the Large Firm workers are the youngest. However, besides this difference, the workers in these clusters work in firms with similar characteristics. Regarding the firm demographic variables shown in the table, none of the differences between these three clusters are statistically significant.

Table 2.2 - Descriptive statistics of clusters obtained via sequence analysis, separating by firm size, calculated at sample entry.

	Cluster						
	Small Firm Workers	Necessity 1	Medium-Sized Firm Workers	Necessity 2	Fast Transitioners	Large Firm Workers	All
Age	28.10	26.86	27.73	28.17	28.52	26.68	27.78
	(5.58)	(5.39)	(5.73)	(5.76)	(5.63)	(5.37)	(5.65)
Higher education	0.19	0.29	0.22	0.18	0.24	0.28	0.23
	(0.39)	(0.45)	(0.42)	(0.38)	(0.43)	(0.45)	(0.42)
Wage (euros)	652.26	979.23	817.88	700.33	772.30	1018.59	809.71
	(458.72)	(2797.97)	(606.47)	(626.73)	(629.74)	(953.31)	(1243.24)
Low skills	0.07	0.11	0.06	0.09	0.06	0.09	0.08
	(0.26)	(0.31)	(0.23)	(0.29)	(0.24)	(0.29)	(0.27)
Medium-low skills	0.62	0.58	0.64	0.62	0.62	0.55	0.61
	(0.48)	(0.49)	(0.48)	(0.49)	(0.49)	(0.50)	(0.49)
Medium-high skills	0.12	0.16	0.14	0.15	0.15	0.18	0.15
	(0.32)	(0.37)	(0.34)	(0.36)	(0.36)	(0.38)	(0.35)
High skills	0.19	0.15	0.17	0.14	0.18	0.18	0.17
	(0.39)	(0.36)	(0.38)	(0.35)	(0.38)	(0.38)	(0.37)
Firm age	9.04	19.01	10.61	11.09	10.02	14.48	12.07
	(22.63)	(31.75)	(13.28)	(26.05)	(23.68)	(17.33)	(23.30)
Firm size (number of employees)	104.63	1086.24	262.12	348.11	157.60	805.71	420.29
	(900.17)	(2899.31)	(1595.28)	(1793.62)	(1023.94)	(2399.80)	(1874.00)
Sales (millions of euros)	9.16	104.41	22.41	33.51	11.55	74.36	38.66
	(99.24)	(407.83)	(200.98)	(244.45)	(129.90)	(316.13)	(249.76)
High-tech manufacturing	0.03	0.04	0.05	0.03	0.03	0.04	0.04
	(0.18)	(0.18)	(0.22)	(0.17)	(0.17)	(0.19)	(0.19)
Low-tech manufacturing	0.07	0.12	0.11	0.09	0.09	0.10	0.10
	(0.26)	(0.32)	(0.31)	(0.28)	(0.29)	(0.29)	(0.29)
Knowledge-intensive services	0.35	0.43	0.32	0.37	0.38	0.45	0.38
	(0.48)	(0.50)	(0.47)	(0.48)	(0.49)	(0.50)	(0.48)
Less knowledge-intensive services	0.43	0.33	0.41	0.43	0.40	0.36	0.40
	(0.50)	(0.47)	(0.49)	(0.49)	(0.49)	(0.48)	(0.49)
Other sectors	0.11	0.08	0.11	0.09	0.11	0.06	0.10
	(0.31)	(0.28)	(0.31)	(0.28)	(0.31)	(0.23)	(0.29)
Median age of firm's workforce	33.44	34.07	34.36	33.60	33.80	33.38	33.85
	(6.48)	(6.11)	(6.35)	(6.31)	(6.22)	(6.23)	(6.29)
Median age of firm's managers	37.61	37.89	38.95	38.55	38.12	37.41	38.22
	(9.10)	(7.20)	(8.87)	(8.63)	(8.74)	(7.87)	(8.43)
Median age of firm's top managers	36.44	36.99	38.84	37.54	37.19	36.55	37.37
	(8.75)	(7.91)	(9.81)	(9.37)	(9.34)	(7.47)	(8.81)
Median age of firm's middle managers	38.33	39.34	39.11	39.03	38.73	38.64	38.95
	(9.50)	(7.73)	(8.77)	(8.68)	(8.65)	(8.08)	(8.52)
Firm's median age at promotion to managerial roles	32.76	33.38	33.66	33.67	33.53	32.70	33.36
	(6.73)	(5.72)	(6.05)	(6.19)	(6.43)	(4.94)	(5.91)
Observations	714	961	1,474	1,366	1,253	639	6,407

Notes: Statistics computed at labor market entry.

To understand if there are observable career differences between top and middle managers, we run extra regressions in which we zoom into the managerial workforce in our sample. Past literature suggests that managers are more likely to become entrepreneurs, but studies separating top and middle managers are rare. To perform these analyses, we run identical regressions as the ones that led to the results shown in Figure 2.1, but using a subsample that considers only workers that are managers at one point during our 10-year period of analysis. Results are shown in Figure 2.3[7]

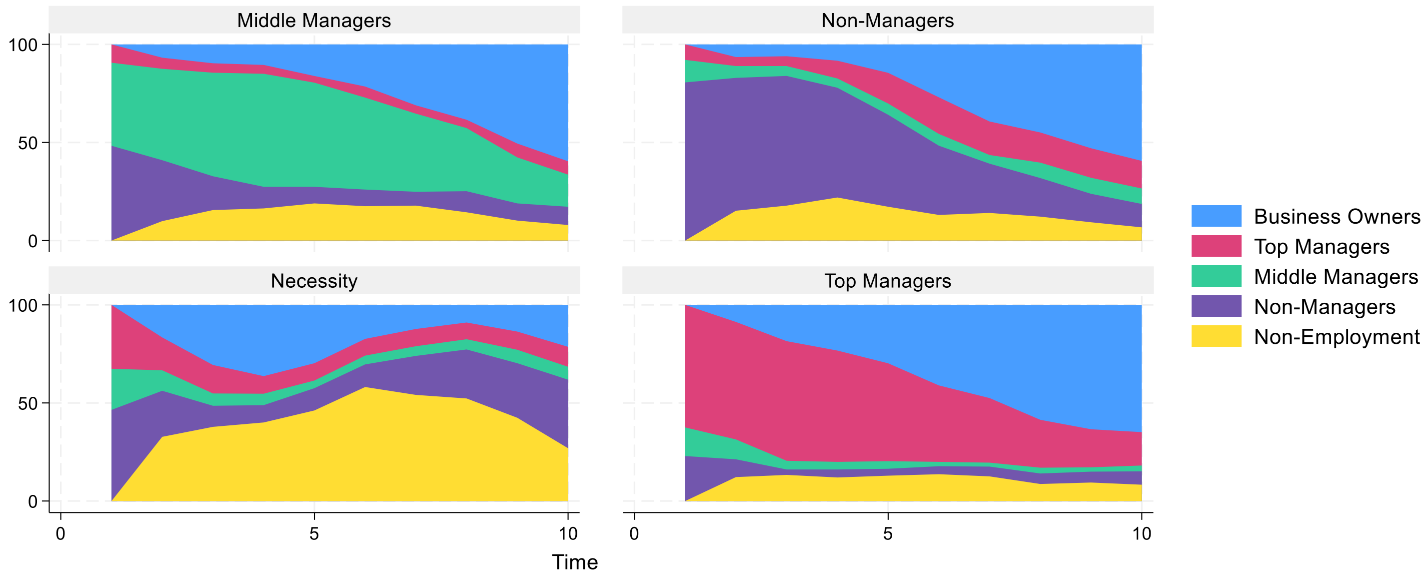

Figure 2.3 – Sequence analysis proportional distribution chronograms by cluster, separating between top and middle managers.

Looking at Figure 2.3, we can see that the cluster in the bottom-left corner is mainly composed of workers who spend a significant amount of time in non-employment, and therefore, we once again call it Necessity. The cluster in the top-left corner is composed largely of workers who are middle managers prior to becoming entrepreneurs, the one on the top-right of non-managers prior to transitioning, and the one on the bottom-right corner of top managers prior to transitioning. Workers in the Top Managers cluster seem to transition into entrepreneurship slightly earlier and with more prominence than workers in the Middle Managers or in the Non-Managers cluster.

Once more, we complement the cluster analysis with descriptive statistics of the cluster, shown in Table 2.3. Analysing Table 2.3, we can see that when comparing the Top Managers with the Middle Managers cluster, the workers in the former are older, more educated, and

[7] See Figure 2.A.3 in Appendix 2.A for the chronograms shown in Figure 2.3, with the absolute number of individuals per cluster.

occupy higher skilled jobs than the latter. However, when looking at the characteristics of the firms where they work at, none of the firm characteristics between the two clusters are statistically different from one another. This suggests that, if top managers are indeed more prone than middle managers to pursue entrepreneurship, it is likely due to reasons not directly connected to the firms in which they work at, but rather with personal characteristics of the workers.

Table 2.3 - Descriptive statistics of clusters obtained via sequence analysis, separating between top and middle managers, calculated at sample entry.

	Cluster				
	Middle Managers	Non-Managers	Necessity	Top Managers	All
Age	28.50	27.66	29.11	30.04	28.79
	(5.13)	(5.08)	(5.32)	(4.88)	(5.19)
Higher education	0.46	0.37	0.43	0.67	0.47
	(0.50)	(0.48)	(0.49)	(0.47)	(0.50)
Wage (euros)	1021.64	934.58	952.74	1451.39	1077.30
	(677.77)	(852.11)	(815.22)	(1319.67)	(976.16)
Low skills	0.02	0.05	0.03	0.01	0.03
	(0.14)	(0.21)	(0.16)	(0.10)	(0.16)
Medium-low skills	0.35	0.53	0.32	0.16	0.35
	(0.48)	(0.50)	(0.47)	(0.36)	(0.48)
Medium-high skills	0.26	0.21	0.20	0.16	0.20
	(0.44)	(0.41)	(0.40)	(0.37)	(0.40)
High skills	0.37	0.22	0.45	0.67	0.42
	(0.48)	(0.41)	(0.50)	(0.47)	(0.49)
Firm age	11.88	12.71	12.19	12.94	12.48
	(16.56)	(22.74)	(25.39)	(28.82)	(24.32)
Firm size (number of employees)	352.28	332.04	318.48	232.36	307.34
	(1841.59)	(1660.12)	(1459.49)	(1358.78)	(1565.60)
Sales (millions of euros)	41.62	31.70	31.98	32.52	33.53
	(247.62)	(181.81)	(234.81)	(255.09)	(227.19)
High-tech manufacturing	0.02	0.04	0.03	0.02	0.03
	(0.15)	(0.19)	(0.18)	(0.14)	(0.17)
Low-tech manufacturing	0.10	0.10	0.09	0.06	0.09
	(0.30)	(0.29)	(0.29)	(0.24)	(0.28)
Knowledge-intensive services	0.43	0.43	0.50	0.56	0.48
	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)
Less knowledge-intensive services	0.36	0.35	0.30	0.28	0.32
	(0.48)	(0.48)	(0.46)	(0.45)	(0.47)
Other sectors	0.08	0.09	0.07	0.08	0.08
	(0.28)	(0.28)	(0.26)	(0.28)	(0.27)
Median age of firm’s workforce	34.07	33.59	34.01	34.55	34.02
	(6.52)	(6.23)	(5.91)	(6.05)	(6.14)
Median age of firm’s managers	36.18	37.22	35.91	35.47	36.20
	(7.87)	(8.67)	(7.92)	(6.93)	(7.91)
Median age of firm’s top managers	34.94	35.63	35.11	35.87	35.39
	(7.69)	(8.91)	(7.52)	(8.14)	(8.11)
Median age of firm’s middle managers	37.99	38.85	36.95	36.02	37.35
	(9.07)	(8.80)	(8.57)	(7.09)	(8.39)
Firm’s median age at promotion to managerial roles	32.30	33.52	31.74	32.74	32.58
	(5.98)	(6.43)	(4.52)	(5.09)	(5.55)
Observations	354	697	669	541	2,261

Notes: Statistics computed at labor market entry.

Lastly, as robustness checks, we rerun all three regressions of this study, but excluding workers that transition into entrepreneurship coming from a non-employment spell, and which start startups with size one. By doing so, we hope to exclude necessity entrepreneurs from the sample of analysis, as such entrepreneurs may become business owners for reasons not related to the accumulation of skills. If that were to be the case, the theory behind the rank effect, which we aim to observe, may not be applicable to these entrepreneurs. The results of these regressions are shown in Figures 2.A.4 to 2.A.6, in Appendix 2.A. The resulting clusters are slightly different than the ones in our main analyses, but the main conclusions we can draw from them remain similar, namely that managers (especially top managers) and small firm workers are more likely to become entrepreneurs than workers with other characteristics.

2.5. Conclusion

This study examines how workers' career trajectories shape their likelihood of transitioning into entrepreneurship, with a particular focus on the roles of managerial experience, firm size, and workforce demographics. By employing sequence analysis, we capture the complexity of these career paths and provide a nuanced understanding of the factors that facilitate entrepreneurial transitions.

By using sequence analysis, which allows us to analyse different stages of workers' careers, we explicitly consider that entrepreneurship outcomes can be shaped by the longer-term impact of cumulative patterns over time (Fuller, 2008), shedding light on how the diversity and complexity of trajectories provide context for explaining transitions to entrepreneurship (Backman et al., 2021). As such, sequence analysis serves as a powerful descriptive method that helps us understand whether workers who accumulate managerial experience, work in smaller firms, or work in firms with younger workforces, are more likely to become business owners.

In accordance with prior literature, our results suggest that managerial experience plays an important role in the career pathways of those individuals who transition to entrepreneurship, compared to others who do not acquire such experience.

Our findings also highlight that workers who do not occupy managerial positions, when compared to those who do, tend to be in firms with older managers, and with older ages of managerial promotion. Such results provide support for the rank effect: as proposed by Liang et al. (2018), older managers may slow down the career progression of younger workers in their firms, making it more difficult for them to reach managerial positions and, consequently, reducing the likelihood of these younger workers to become entrepreneurs. Since we find that employees who do not occupy managerial positions are less prone to transition to entrepreneurship, these characteristics of the firms in which they are employed suggest that these mechanisms of the rank effect may be taking place in our sample.

We also show that top managers transition to entrepreneurship at higher rates than middle managers, and do so earlier. However, the firms in which both manager types work are not significantly different, which suggests that there may be inherent differences between these two groups of workers, that would explain why top managers are more likely to create their own firms. This finding opens possibility for future studies in this topic, which has been underexplored in past literature.

Lastly, our results also suggest that working in smaller firms may be positively correlated with entrepreneurial transitions, as predicted by the small firm effect.

Even though sequence analysis works as a powerful descriptive tool of workers' careers, it does not allow us to separate the role of the variables we examined from other factors related to entrepreneurial activity, such as age and human capital, which managers also seem to have more than non-managers. This provides motivation for a deeper look into the link between the demography of firms, the likelihood of occupying managerial positions, and the likelihood of transition to entrepreneurship.

We encourage an important extension to this study. Our chronograms seem to indicate that careers that lead into entrepreneurship do not always follow smooth patterns, with workers transitioning into and from business ownership. By also taking advantage of sequence analysis, future studies can examine these trends (as done by Koch et al., 2021), trying to understand what types of prior career paths and work experience are connected with more or less stable career development paths.

2.A. Appendix

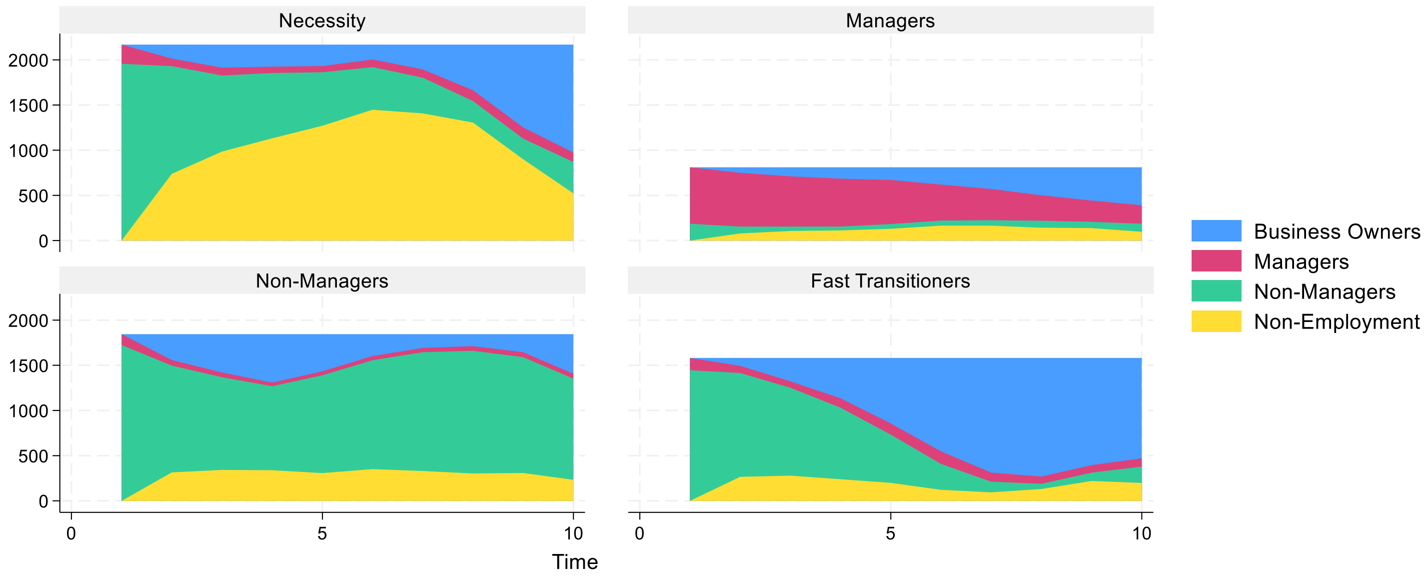

Figure 2.A.1 - Sequence analysis distribution chronograms by cluster, with the absolute number of individuals per cluster.

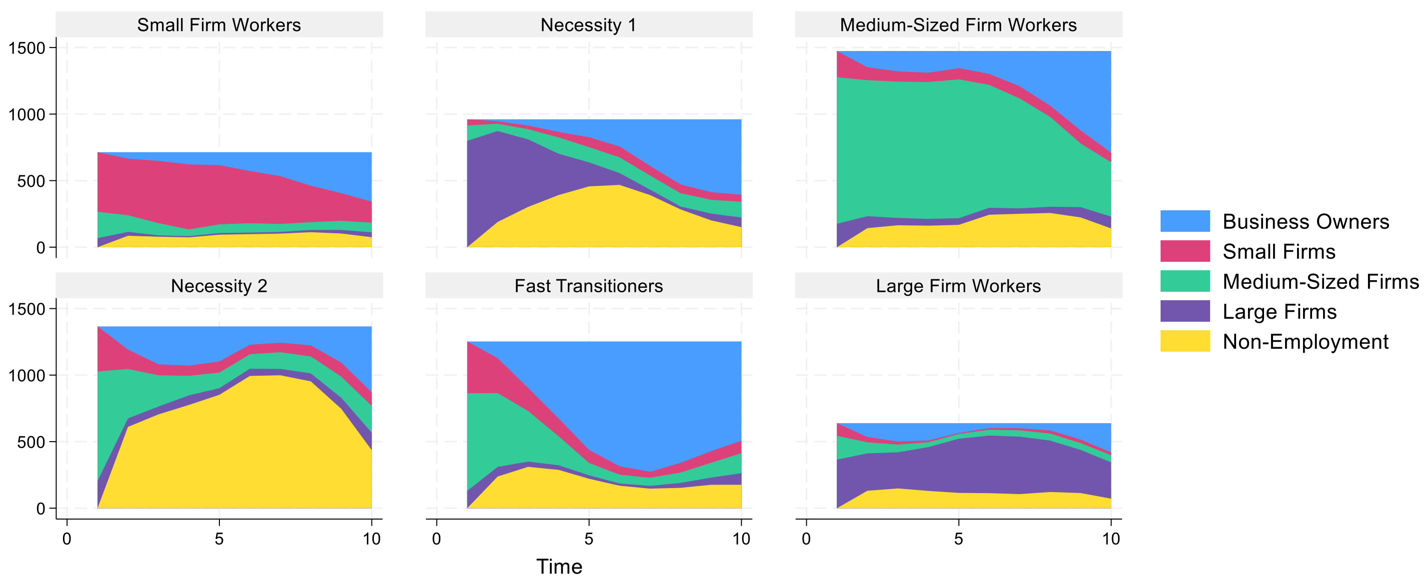

Figure 2.A.2 - Sequence analysis distribution chronograms by cluster, separating by firm size, with the absolute number of individuals per cluster.

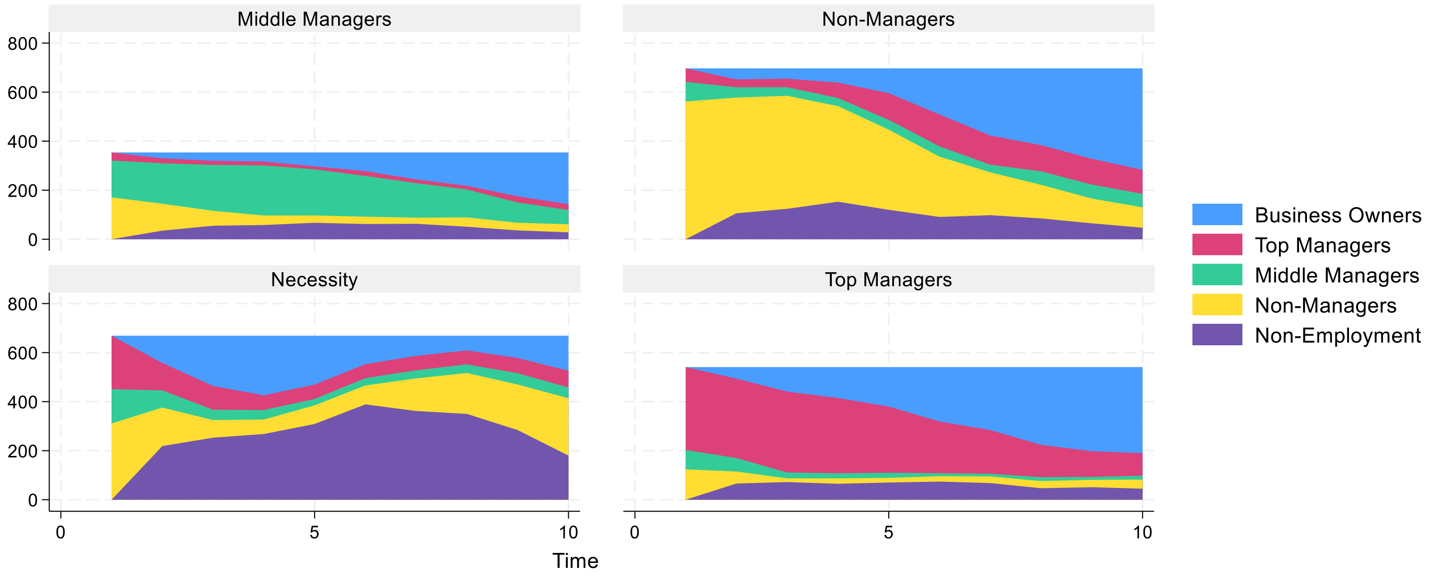

Figure 2.A.3 – Sequence analysis distribution chronograms by cluster, separating between top and middle managers, with the absolute number of individuals per cluster.

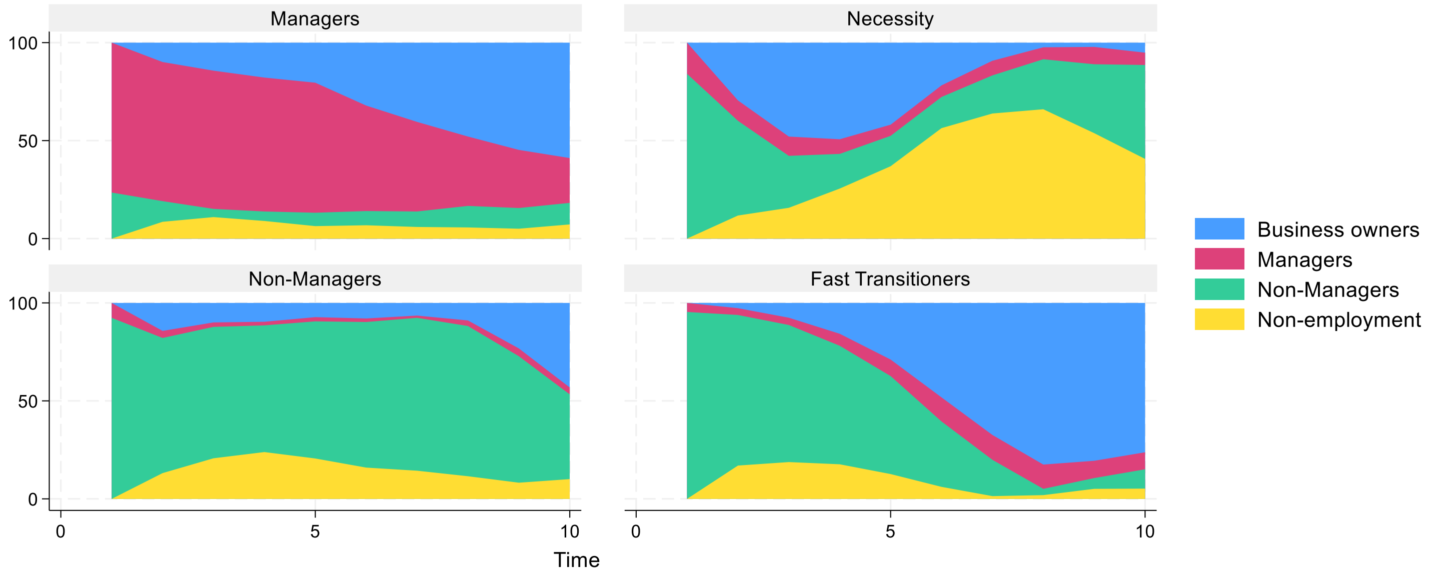

Figure 2.A.4 - Sequence analysis proportional distribution chronograms by cluster, excluding self-employed individuals who transition from non-employment.

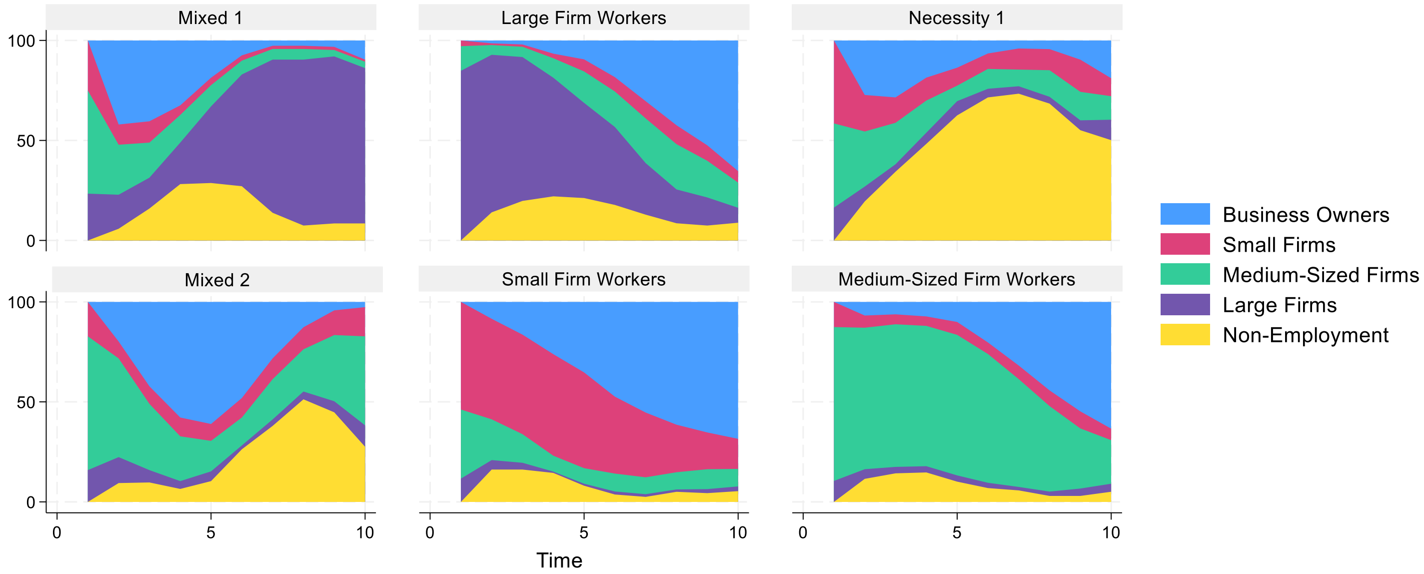

Figure 2.A.5 - Sequence analysis proportional distribution chronograms by cluster, separating by firm size, excluding self-employed individuals who transition from non-employment.

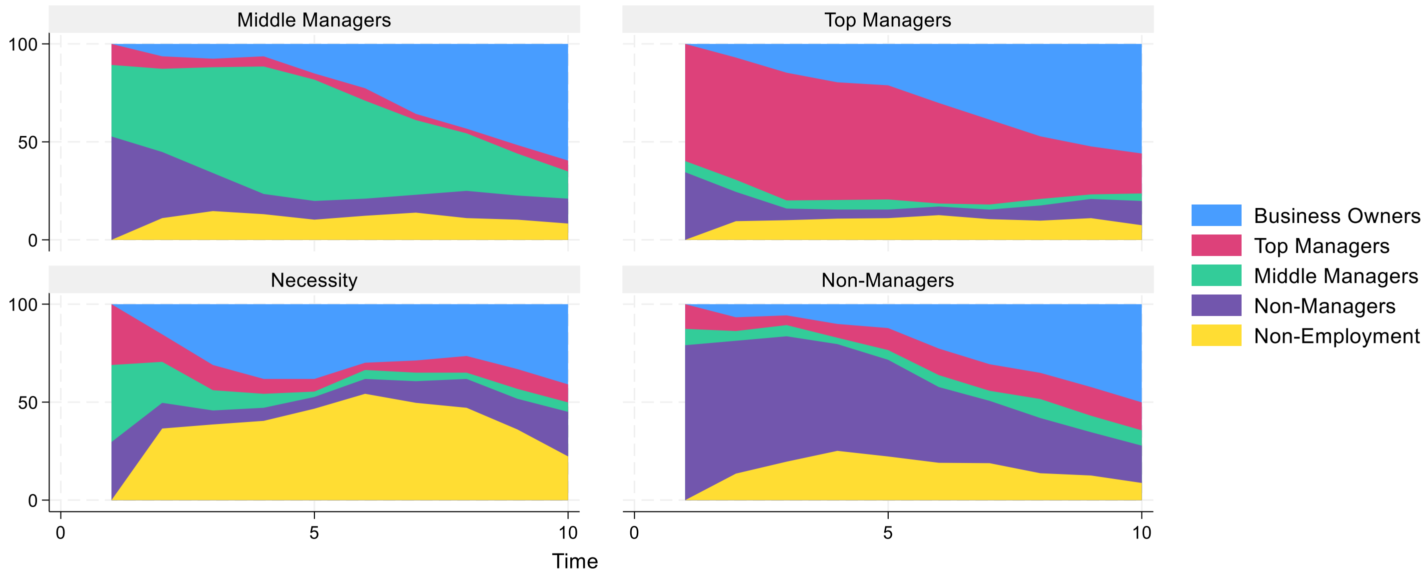

Figure 2.A.6 – Sequence analysis proportional distribution chronograms by cluster, separating between top and middle managers, excluding self-employed individuals who transition from non-employment.

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Chapter 3

The Entrepreneurship Fountain of Youth: Younger Management Ranks Generate More Entrepreneurs[8]

3.1. Introduction

Rapidly aging workforces put pressure on countries, especially in Europe, to deal with challenges such as increases in health care and social security costs and decreases in the labor supply. Workforce aging may also suppress entrepreneurship rates (Lévesque & Minniti, 2006; Liang et al., 2018) which could slow down job creation and innovation. Against this background, youth entrepreneurship is high on the EU political agenda as part of the Europe 2020 growth and jobs strategy.[9]

Workforce aging reduces entrepreneurship as individuals may be less willing to invest time in starting their own firm when they get older. Relevant skills (e.g., creativity and willingness to take risks) and incentives for entrepreneurship decline with age (Lévesque & Minniti, 2006). Liang et al. (2018) develop a rank effect theory proposing that aging of managerial workforces is at play in lowering entrepreneurship. Entrepreneurs commonly work as wage employees for several years before starting a business (Evans & Leighton, 1990) and when gaining experience working as managers they likely build up relevant knowledge, skills and capabilities for entrepreneurship (Lucas, 1978; Dobrev & Barnett, 2005; Cassar, 2006; Staniewski, 2016; George et al., 2022).[10] According to the rank effect, with aging workforces, older workers will occupy and hold on to key managerial positions within firms. This will slow down the career progression of younger workers who are then only able to gain managerial experience that is

[8] This paper has been published in the Journal of Business Venturing, 40(4), from July 2025.
[9] See https://youth.europa.eu/strategy/employment-entrepreneurship_en.
[10] Examples of managers of established firms who become entrepreneurs are too many to count. Zoom founder, Eric Yuan, was a corporate vice president for Cisco Webex. Clay Bavor, who co-founded Sierra, was at Google for 18 years, overseeing projects such as Gmail, Google Docs, and Google Drive. Falguni Sanjay Nayar, founder of Nykaa and one of two self-made female billionaires in India, was previously a managing consultant and investment banker; Whitney Wolfe Herd, founder of Bumble, was vice-president of marketing for Tinder.

valuable for entrepreneurship later in their lives and this will result in lower entrepreneurship rates across the whole age spectrum.

Although Liang et al. (2018) do not specify what constitutes key managerial experience, arguably experience in top and middle management roles is most relevant for entrepreneurship. The high levels of responsibility that come with top and middle management roles allow workers to accumulate experience in defining, coordinating and supervising the firm's fundamental activities, and in making decisions based on external conditions (Raes et al., 2011). By performing top and middle management roles, workers develop dynamic managerial capabilities (Heaton & Teece, 2013) and acquire the skills required to recognize and develop innovative business opportunities, formulate strategies, and acquire resources (Oberschachtsiek, 2012). Top management experience may be especially valuable for entrepreneurship, for example, because top manager's responsibilities regarding strategic decision-making under uncertainty are more akin to those of entrepreneurs (Mintzberg, 1973), when compared to the tasks performed by middle managers, like supervising and monitoring employees and daily tasks (Floyd & Wooldridge, 1997).

The present study tests the presence of the rank effect by examining whether firms with older top and middle managers provide less opportunities for their employees to reach such top and middle management roles and whether this, in turn, makes it less likely for employees of such firms to become entrepreneurs. We provide a novel and comprehensive test of the rank effect, that is, while Liang et al. (2018) link country-level demographics to entrepreneurship rates, we adopt a more granular approach by examining the impact of firm demographics on employee's decisions to exit the firm and become an entrepreneur.

According to rank effect theory, non-managerial workers may be impeded in their career progression in firms with aging managers. While slow career progression possibly leads to frustration and may push non-managerial workers into entrepreneurship (Kacperczyk & Marx, 2016), these workers may instead choose to take on new jobs as employees in other firms. We therefore test to what extent these two career changes occur and whether they are related with slow career progression. In this way, we contribute to the debate on whether potentially frustrated workers become entrepreneurs.

We test our ideas by estimating discrete-time hazard models using *Quadros de Pessoal*, a longitudinal matched employer-employee database covering the Portuguese economy that provides detailed information at both the firm-level and the worker-level. Portugal provides an interesting context for our study as it is one of the fastest aging countries in Europe and, at the same time, one of the countries with the highest rates of firm creation.[11] Finding significant evidence of the existence of the rank effect in this setting would suggest that a rapidly aging workforce is likely to slow down entrepreneurship even when firm birth rates are relatively high.

Our results provide support to rank effect theory. In firms with older managers, employees have a lower probability of becoming entrepreneurs than in firms with younger managers. This negative relationship between managerial workforce age and entrepreneurship can be explained by the fact that employees are less likely to access top and middle management positions in firms with older managers. This result is most pronounced when firms have older top managers suggesting that older top managers have a greater influence on blocking internal career progression (and hence on reducing entrepreneurship) compared to older middle managers. While we validate the importance of managerial experience in transitioning to entrepreneurship, we also find that top managers are more likely to move to entrepreneurship than middle managers. Lastly, we find that employees who progress slower than average towards a managerial role, and hence may be frustrated in their careers, are likely to seek a new job rather than becoming an entrepreneur or staying with the firm. In sum, our findings suggest that firms with younger top and middle managers have a culture involving younger people in key managerial positions and, through this, generate more entrepreneurs.

Our study contributes to the literature on age and entrepreneurship by showing that the age of a firm's workforce impacts the likelihood that the firm will spawn entrepreneurs. Moreover, we show that holding a managerial position represents an indirect channel through which workforce aging affects entrepreneurship. We extend rank effect theory by proposing and showing that it especially holds when firms have older top managers (significantly more so than when a firm's middle managers are older). We add to the literature on career paths leading to entrepreneurship (Kim et al., 2006; Burton et al., 2016) and to the research on the relationship between dynamic managerial capabilities and entrepreneurship (Staniewski, 2016; George et al., 2022) by showing that experience in middle and (especially) top management positions, and early access in one's career to such key management positions, is a vital path leading to entrepreneurship.

[11] As of 2021, Portugal had the third highest share of the population aged 65 or more in Europe (Eurostat, 2022a). Also, as of 2019, it was the second country in Europe with the highest firm birth rate, as measured by the ratio between the number of new firms and the total number of active firms (Eurostat, 2022b).

The rest of the paper is structured as follows. In Section 3.2 we consider the background for the study and develop hypotheses regarding the relationship between the rank effect, workers' access to managerial experience, and career transitions into entrepreneurship. Section 3.3 introduces the data and methodologies used in the study. In Section 3.4 we present the results of econometric hazard models examining the hypotheses advanced in Section 3.2. In Section 3.5 we discuss our results while Section 6 concludes.

3.2. Background and Hypotheses

Rank effect theory (Liang et al., 2018) describes how aging of a firm's (managerial) workforce results in a decline in entrepreneurship by lowering the number of individuals that reach managerial ranks. We first explore how experience in managerial positions relates to entrepreneurship (Section 3.2.1); next we discuss how aging of a firm's managerial workforce relates to entry into entrepreneurship (3.2.2); we then look at how career delay in reaching entrepreneurial ranks will affect career changes including the choice to become an entrepreneur (3.2.3); lastly, we discuss how experience in top management roles differs from that obtained in middle management roles and what this implies for transitions into entrepreneurship.

3.2.1. Managerial Experience, Dynamic Managerial Capabilities and Entrepreneurship

Entrepreneurs often work as wage employees for several years before founding their own businesses (Evans & Leighton, 1990; Dobrev & Barnett, 2005; Sørensen & Fassiotto, 2011). Past research posits that experience gained in employment, particularly in managerial roles, can be crucial for entrepreneurship (Agarwal et al., 2004; Franco, 2005). Managerial positions help develop strategic decision-making, resource management, and leadership skills, which are essential for entrepreneurship (Lucas, 1978; Dobrev & Barnett, 2005; Cassar, 2006; Kim et al., 2006; Staniewski, 2016; George et al., 2022). Rank effect theory (Liang et al., 2018) builds on the idea that managerial experience is valuable for entrepreneurship.

The concept of dynamic managerial capabilities is understood as "the capabilities with which managers create, extend, and modify the ways in which firms make a living" (Helfat & Martin, 2015:1281). Managers are responsible for refreshing and transforming the resource base of their firms by carrying out activities consisting of sensing and seizing opportunities and transforming the resource base (Ambrosini & Altintas, 2019). By performing such actions, managers are especially likely to accumulate specific skills and experiences that are relevant for entrepreneurship (Heaton & Teece, 2013; Andersson & Evers, 2015; George et al., 2022).

We argue that managers are more likely than other workers to develop the capabilities required to recognize and develop innovative business opportunities, formulate strategies, and acquire resources (Oberschachtsiek, 2012), making them more likely to become entrepreneurs. Managers should therefore possess an enhanced ability to discover, create, and exploit opportunities by increasing their market knowledge, alertness to external conditions, and access to social networks (Kirzner, 1997; Shane, 2000; Ozgen & Baron, 2007; Sarasvathy, 2008; Alvarez et al., 2013; Davidsson, 2015). Managers are also more likely to be able to mobilize and accumulate resources that are crucial to new venture creation (Colombo et al., 2004; Heaton & Teece, 2013; Andersson & Evers, 2015; George et al., 2022).

Managers also acquire experience in decision-making roles that is not accessible to subordinate employees, including supervising and coordinating teams, setting objectives and deadlines, and rewarding performance. They gain practice in conflict handling between subordinates, mentoring and training workers, and giving feedback to or even firing underperforming employees. Through these activities, managers are able to acquire more balanced knowledge about multiple functions within the firm, rather than sticking to knowledge that is specialized in a single function (Burgoyne & Stuart, 1976). These balanced, general skills developed by managers can spur innovation (Custódio et al., 2019) and are also found in entrepreneurs (Lazear, 2005; Stuetzer et al., 2013).

We argue that managerial experience and, in particular, dynamic managerial capabilities are key to opportunity identification and development of operational strategies. Experience in opportunity recognition, resource mobilization, organization and supervision likely increases the chances for workers with top and middle management experience to become entrepreneurs. Therefore, based on the above discussion, we state the following hypothesis.

Hypothesis 1: Workers who have reached top and/or middle management roles are more likely to become entrepreneurs compared to non-managerial workers.

3.2.2. Workforce Age and Entrepreneurship

Age is one of the most studied individual level variables when examining transitions to entrepreneurship (Parker, 2005). Several studies find that the relationship between age and entrepreneurship takes an inverted U-shape (Bönte et al., 2009; Minola et al., 2016; Azoulay et al., 2020), because some determining factors that are positively related with the probability of transitioning into entrepreneurship improve with age while others decline with it. Most studies find that the turning point for this relationship (from positive to negative) occurs between the mid-30s and mid-40s (Carrasco, 1999; Amaral & Baptista, 2007; Tag et al., 2016). Thus, individual propensities to become an entrepreneur decline after a certain age.

Liang et al. (2018), in a theory they coined the rank effect, predict that with an aging workforce, top and middle managers are older and remain in their positions for longer, thereby blocking the progression of (likely younger) non-managers and barring them from obtaining managerial experience that is useful for entrepreneurship. As a consequence, entrepreneurship rates will decline. Simultaneously, as workers accumulate experience in non-managerial positions, they collect firm-specific, specialized experience that is more valuable within the firm rather than general managerial experience that should be valuable for entrepreneurship (Lazear, 2005; Stuetzer et al., 2013), leading to higher opportunity costs of entrepreneurship, further decreasing their likelihood of becoming entrepreneurs.

In firms where workers reach top and middle management ranks at later ages, younger, potentially more innovative and less risk-averse individuals will lack skills, knowledge and capabilities that are specific to top and middle managers and relevant for entrepreneurship. If individuals can only gain top and middle managerial experience later in their professional lives, they may never engage in entrepreneurship as, by that time, the opportunity cost of abandoning an established corporate career may be too high. In general, as tenure increases and job rank improves, wages increase, and workers are less likely to exit the firm (Baker et al., 1994a,b). Firm-level evidence supporting this proposition is provided by Bianchi et al. (2023). These authors find that an increase in mandatory retirement age – leading to extended tenure by older employees – caused delays in the promotions of younger workers in Italian firms. These authors also find that even if promotions in a firm are being blocked by the presence of older workers, younger workers are unlikely to leave for other firms, as they might have to enter at lower positions in the career ladder.

In contrast, in firms where younger subordinates have greater chances of holding managerial positions, these employees are more likely to learn skills that are important for entrepreneurship, while being young enough that qualities such as creativity, flexibility, and ability to take risks have not yet eroded with age, leading to higher likelihoods of entrepreneurial transitions. This creates more openings for managerial positions to be filled, possibly by other younger non-managers, who would then be able to accumulate managerial capabilities and potentially transition to entrepreneurship themselves.

To summarize, we expect that firms with older top and middle managerial workforces will spawn less entrepreneurs. We thus hypothesize the following:

Hypothesis 2a: Working at a firm where the top managers are older decreases the probability of employees becoming entrepreneurs, by lowering their chances of reaching top and middle management ranks.

Hypothesis 2b: Working at a firm where the middle managers are older decreases the probability of employees becoming entrepreneurs, by lowering their chances of reaching top and middle management ranks.

3.2.3. Career Delay and Entrepreneurship

The perception that access to managerial levels is impeded or delayed may lead workers to seek alternative career paths. The lack of promotion opportunities may increase turnover, as younger employees seek career advancement elsewhere. Research shows that employees are more motivated and productive when they perceive a clear path for career advancement (Locke & Latham, 1990). However, in firms with aging managerial structures, younger workers may feel trapped in their current roles and experience increased job dissatisfaction, as they perceive a disconnect between their ambitions and the opportunities available to them within the organization (Greenhaus et al., 2000). Such dissatisfied workers are more likely to leave organizations that do not offer clear paths for growth (Cennamo & Gardner, 2008).

Kacperczyk and Marx (2016) find that entrepreneurs often emerge from smaller firms because these firms provide fewer opportunities for career progression. This finding indicates that there could be a push-factor that leads workers who cannot be promoted in a firm to leave it, possibly going into entrepreneurship. Similarly, Sorensen and Sharkey (2014) state that when career growth in established firms stagnates, workers become more prone to transition to entrepreneurship. Moreover, if changing from one firm to another as a wage worker is constrained by limited opportunities, workers may become entrepreneurs when this becomes the most attractive available option.

However, several studies indicate that the lack of career growth opportunities could also lead workers into changing firms as wage employees, rather than becoming business owners. Sorensen and Sharkey (2014) stress that employees facing lack of advancement opportunities may become dissatisfied and end up leaving the firm in which they work for another one. Pergamit and Veum (1989) find a positive correlation between promotions and job satisfaction, which in turn is negatively correlated with employee turnover. Hyter (2007) finds that firms increase their employee retention rate by providing more opportunities for the growth of employees' careers. All these findings suggest that push-factors associated with lack of promotion opportunities are likely to lead workers to change jobs to other firms, as wage workers rather than as entrepreneurs.

Based on this discussion, it can be claimed that workers who experience or perceive a delay in reaching managerial levels are more likely to leave the firm than other employees, finding employment in another firm or becoming entrepreneurs. There are several parallels between mobility to other firms and mobility to business ownership. Both depend on opportunities, job-relevant resources, constraints, and professional networks (Rosenfeld, 1992). According to the theory of planned behaviour (Ajzen, 1991), such decisions are influenced by subjective norms, perceived desirability, and readiness for change. While we expect entrepreneurship to be more attractive to wage workers who have acquired managerial experience, as proposed by rank effect theory, workers frustrated by delayed promotions may also view entrepreneurship, as well as employment in other firms, as a viable alternative. It is therefore relevant to examine the impact of delayed advancement on career mobility. Based on this discussion, we test the following two opposing hypotheses.

Hypothesis 3a: Workers who take longer to reach top and middle management positions than the average number of years it took other workers in the firm to reach those positions, are more likely to become entrepreneurs than other workers.

Hypothesis 3b: Workers who take longer to reach top and middle management positions than the average number of years it took other workers in the firm to reach those positions, are more likely to transition into a new job in another firm than other workers.

3.2.4. Top vs Middle Management

Our research innovates by focusing on and distinguishing between top and middle managers. While top and mid-level managers perform different tasks, we argue that both are likely to develop capabilities that contribute to entrepreneurship. Top (strategic) managers play a crucial role in driving innovation and navigating the complexities of environmental dynamism. By operating in a distinct hierarchical tier, between top managers and supervisors, middle managers translate strategic signals into practical actions, sensing opportunities and devising innovative solutions, thus developing dynamic managerial capabilities that are distinct from those of top managers (Felin et al. 2015; Helfat & Martin, 2015). Such capabilities are likely relevant for entrepreneurship as middle managers' proximity to both workers and customers positions them as key conduits for innovation, identifying unmet needs and process inefficiencies that could serve as the foundation for entrepreneurial ventures (Burgelman, 1983).

While top and middle managers may pursue different kinds of new ventures, both are likely to have privileged access to profitable entrepreneurial opportunities, making them more likely to become entrepreneurs than non-managers. However, top and middle managers develop distinct skillsets, which may influence their entrepreneurial propensity differently. In particular we expect top managers to have a higher propensity for entrepreneurship than middle managers.

Firstly, the tasks and responsibilities of top managers are, to some extent, similar to those required for entrepreneurship. Top managers, like entrepreneurs, are responsible for overseeing a firm's financial sustainability and need to make strategic decisions under uncertainty. Unlike middle managers, top managers gain experience with taking on complex and risky projects, with commanding resources, and with displaying organizational leadership (Mintzberg, 1973). Top managers are responsible for setting a company's vision, defining long-term goals, and overseeing resource allocation and stakeholder relationships (Hambrick & Mason, 1984). Top managers drive innovation processes, through decisions on internal development, outsourcing, corporate ventures, acquisitions, or strategic alliances, all while monitoring market and technology trends to identify large-scale business opportunities. Their extensive networks, leadership skills, and ability to manage complex projects suggest a natural inclination towards entrepreneurial activities (Mintzberg, 1973). The financially secure position associated with their roles also likely reduces the risk of entering entrepreneurship. Middle managers translate corporate strategy into actionable plans, managing teams, and ensuring that day-to-day operations align with organizational objectives (Floyd & Wooldridge, 1997). Thus, they have a highly internal focus supervising employees and coordinating communication between different departments within the organization and entrepreneurship may often require them to think beyond daily operations in order to conceptualize and implement a new idea, product, or service. Middle managers take directives from senior leadership meaning that they typically have less autonomy, which can limit their ability to explore entrepreneurial opportunities which often require independent and bold decisions.

Secondly, top managers' externally oriented role likely provides more exposure to and awareness of outside opportunities stemming from technology and market trends, unlike middle managers, who are more focused on internal operations. Dobrev and Barnett's (2005) findings go in accordance with this: top managers are always more likely than other workers to become entrepreneurs. Indeed, top managers likely have more access to funding and relevant networks for entrepreneurship compared to middle managers. In contrast, middle managers professional networks are likely more limited, making it harder to access the resources and guidance to start a business.

Thirdly, middle managers that aspire to become top managers themselves are likely to keep on climbing the corporate ladder, rather than trying entrepreneurship, even if their career progression is slow (Peter & Hull, 1969). Top managers occupying the highest organizational ranks have no room for further internal career progression, so entrepreneurship may be an attractive next step, allowing them to leverage their skillset and expertise. While the financial and prestige-related opportunity costs of leaving top positions may deter top managers from pursuing entrepreneurship (Smith et al., 2005), top managers are also likely to be better able to command resources and less likely to face financial constraints when starting a new business (Baptista et al., 2014).

Taking all this into account, we posit the following hypothesis:

Hypothesis 4a: Top managers are more likely to become entrepreneurs, compared to middle managers.

As stated in Hypotheses 2a and 2b, we expect that the age of the managerial workforce is negatively related to the probability of entrepreneurship via reduced chances of reaching managerial positions. We also expect that the age of top managers should have a stronger negative impact on the probability of employees becoming entrepreneurs than the age of middle managers.

When top managers hold on to their positions, they create a bottleneck effect in the promotion pipeline, leaving middle managers with limited opportunities for promotion (Sturman, 2003). This leads to the career stagnation of middle managers which, in turn, limits the opportunities for younger, non-managerial workers to ascend to managerial ranks. Such stagnation can lead to skill obsolescence, as middle managers may not have the opportunity to take on new challenges or develop new competencies that are required for senior leadership roles (Kraimer et al., 2011). Additionally, when middle managers are stagnant, they may lack the enthusiasm or capacity to effectively mentor younger employees, further hindering the career development of non-managerial workers (Liden et al., 2000).

Furthermore, the broader decision-making authority of top managers compared to middle managers also likely plays a key role in making their influence more decisive. Top managers make strategic decisions about the firm's direction, structure, and policies, which include decisions on hiring and promotions. Top managers may have specific views about the types of leaders they want, which can limit internal progression opportunities. They have a broader power to block internal progression, and middle managers will need to align with their views or decisions. Upper echelon theory suggests that top managers leave an imprint on the organization by shaping organizational outcomes (Hambrick & Mason, 1984). Older, more conservative, top managers may prefer people similar to them in lower-level managerial positions. Conversely, if top managers are young and progressive, this will also likely have a strong influence on the organization, since middle managers will have to support their views.

Given these arguments, we expect the age of top managers to have a relatively stronger negative effect on employees' chances of becoming entrepreneurs than the age of mid-level managers, since older top managers represent a stronger barrier to career progression which is felt at all lower levels of the organization. We therefore hypothesize the following:

Hypothesis 4b: The age of top managers has a stronger negative impact on the probability of employees becoming entrepreneurs by lowering their chances of reaching top and middle management ranks, than the age of middle managers.

3.3. Data and Methodology

3.3.1. Data

3.3.1.1. Sample Construction

We use *Quadros de Pessoal* (QP), a longitudinal matched employer-employee dataset containing detailed information on private firms with at least one wage earner, and their employees in the Portuguese economy (excluding the primary sector). The dataset originates from administrative data collected by the Portuguese Ministry of Employment and Social Security through a mandatory yearly survey.

The original dataset accounts for over 2.5 million workers in more than 300 thousand distinct firms per year. At the worker level we have data on age, tenure, education, gender, wages, occupation, and a variable for hierarchical position which allows us to identify workers in top and middle managerial positions. At the firm level, we have information on firm age, number of employees, industry, and region. QP has been extensively used in researching new firm creation and entrepreneurship (e.g., Mata & Alves, 2018; Rocha et al., 2018; and Carias et al., 2023).

We focus on individuals starting a new job spell as wage workers between 2005 and 2015. Each worker is followed until 2019 (the last year of data available to us), except for those who change to other firms, transition to entrepreneurship, become unemployed or exit the workforce. We consider only the most recent job spell that each worker has within this period to avoid issues arising from multiple, non-independent spells of the same worker. With this sampling method we can track individuals in a wide range of career stages, from those in the early stages of their careers to those nearing retirement. We can thus assess how our variables of interest impact the likelihood of transitioning to entrepreneurship for people of different ages, in different career stages.

Our sample includes workers who have completed at least one job spell prior to the period under analysis, so we can gather information on their past experience that enables us to address issues of endogeneity in our empirical analysis (see Subsection 3.2.3).

3.3.1.2. Variables and Descriptive Statistics

The data distinguish between wage workers and business owners (entrepreneurs), allowing us to observe transitions between wage employment and entrepreneurship. Following previous work using the same data source (e.g., Kallmuenzer et al., 2021; Ribeiro et al., 2022), we classify individuals as entrepreneurs if they are identified as business owners of a firm. Our main dependent variable reflects an individual's transition from wage work to entrepreneurship. This is a binary variable and takes the value 0 when an individual is in paid employment and the value 1 if an individual has switched to entrepreneurship.

Rank effect theory implies that managerial experience is an important determinant of entrepreneurship, and we test whether managers are indeed more likely to become entrepreneur than non-managers (see Hypothesis 1). We classify managers as workers who occupy top and middle management roles, and we classify the remaining workers as non-managers.[12]

Also based on rank effect theory, we propose that firms with older managers will have fewer employees who become entrepreneurs, since the probabilities of reaching management

[12] The hierarchical level variable in QP data includes the following levels: top managers; middle managers; supervisors/foremen; higher-qualified professionals; qualified professionals; semi-qualified professionals; non-qualified professionals; and apprentices/trainees. We consider top and middle manager positions as more likely to provide experience relevant for entrepreneurial activities. Accordingly, for the purposes of our analysis we do not consider supervisors/foremen as managers.

ranks will be lower in such firms (see Hypotheses 2a and 2b). We capture the age of the firm's top and middle managers in two ways: 1) by looking at their median age; 2) by looking at the median age at which workers in a firm are promoted to top and middle management positions.

Table 3.1 shows descriptive statistics of the estimation sample. The mean age of the middle managers is 36.01 years, similar to the mean age of the workers in the sample (36.51 years old). Top managers are only slightly older, with a mean age of 37.07 years. The mean age at which workers transition to entrepreneurship is 35.52 years old, also similar to the mean age of the sample. In the period of analysis, 3.36% of the top managers and 2.20% of the middle managers in our sample become entrepreneurs, while only 0.8% of the employees who do not reach managerial roles move to entrepreneurship. While the overall share of individuals who transition to entrepreneurship is low, top managers are 4.2 times more likely than non-managers to become entrepreneurs, while middle managers are 2.8 times more likely to shift towards entrepreneurship. This suggests that managerial experience increases the likelihood of entrepreneurial transitions. Moreover, since top managers seem more likely than middle managers to become entrepreneurs, this may also indicate that those at the very top of firms' hierarchies are better able to identify entrepreneurial opportunities (or exposed to more entrepreneurial opportunities), and are endowed with higher levels of human, social, and financial capital (see Hypothesis 4a). We also create a dummy variable which is equal to 1 if the worker has not reached managerial levels after being in the firm longer than the average time taken by workers who started at the same level to be promoted to management, and 0 otherwise. This variable, which we name "Is Frustrated", accounts for whether the worker is possibly dissatisfied with lack of career progress in the firm. As we can see, 23,094 employees in our sample are frustrated in at least one of their observations, which accounts for 7.1% of the employees.

Higher ability individuals are more likely to become top managers, which in turn may increase their chances of transitioning to entrepreneurship, creating a source of endogeneity. To address this issue, we first obtain estimates of worker and firm fixed effects from a high-dimensional fixed-effects wage regression[13] (see Abowd et al., 1999). We include the estimated worker and firm fixed effects in our regressions for transitions to entrepreneurship to account for potential endogeneity due to unobserved heterogeneity. The worker fixed effect measures wages due to the unobserved ability of the worker, regardless of the characteristics of the firm

[13] Results of the high dimensional fixed-effects regressions are shown in Table 3.A.1 in Appendix 3.A.

in which they work, and excluding the effect of the worker-level controls included in this regression (Abowd et al., 1999; Iranzo et al., 2008; Bender et al., 2018). To identify the fixed effects, we restrict the data to include only the largest connected set of workers, dropping approximately 0.1% of observations, resulting in the sample size presented in Table 3.1.[14]

Table 3.1 - Descriptive statistics of the estimation sample.

Age of workers (years)	36.51 (9.17)
Age of top managers	37.07 (7.54)
Age of middle managers	36.01 (7.57)
Age when transitioning to entrepreneurship	35.52 (8.01)
Years in managerial roles, prior to transition to entrepreneurship	2.69 (2.12)
Number of observations	1,248,652
Number of employees	324,487
Number of firms	48,212
Number of top managers	31,090
Number of middle managers	26,272
Number of employees transitioning to entrepreneurship	3,942
Number of top managers transitioning to entrepreneurship	1046
Number of middle managers transitioning to entrepreneurship	578
Number of frustrated employees	23,094

Notes:Mean values and standard deviations (in parentheses).

Our analysis also accounts for variables commonly used in occupational choice studies such as the logarithm of tenure, age (in both linear and quadratic form), gender, education level, logarithm of firm size (number of employees), technological intensity, year dummies, and region. Finally, to take into consideration workers' labor market history, a series of individual-level variables related to the ten years prior to entering the sample are included: the number of years worked, number of firms the individual worked for, number of years in self-employment, highest skill level of a job (according to ISCO-08), and a variable indicating whether the worker is starting this job spell coming from non-employment.

[14] The largest connected set comprises the subset of observations for which the fixed effects are jointly identifiable. In models with multiple fixed effects—such as worker and firm—identification requires links across units, typically via worker mobility between firms, as in Abowd et al. (1999). While multiple such groups (connected sets) may exist in the data, fixed effects can only be identified within each group. We focus on the largest of these sets, i.e., the group containing the most observations for which the effects are estimable. Observations outside this set are excluded from the estimation, as their fixed effects are not identified. The sample for the high-dimensional fixed-effects wage regression spans the years 1995 to 2019 to ensure enough mobility of workers across firms.

3.3.2. Methodology

3.3.2.1. Hazard Models for Transitions to Entrepreneurship

To study transitions to entrepreneurship, we estimate several specifications of discrete-time hazard models.[15] The choice of a discrete-time model is due to the yearly nature of our dataset. The data are collected on a yearly basis, and hence we do not know the exact moment between these time periods when a transition to entrepreneurship occurs ("interval censoring"). In other words, a discrete-time model is the appropriate model in our case (Allison, 1982).

We use the common formulation of a discrete-time proportional hazard model proposed by Prentice and Gloeckler (1978), which reformulates the basic hazard model to follow a cloglog binary dependent variable specification, the discrete-time equivalent to the continuous-time proportional hazards model (van den Berg, 2001).[16] In addition, cloglog models are usually a better choice than logit models when the event being analyzed happens rarely (Buckley & Westerland, 2004), as is the case in this study (see Table 3.1).

The hazard of transitioning from wage work into entrepreneurship is the probability of that transition taking place at time t, conditional on not having transitioned before t. In our case, t is the tenure in the firm, which represents the time at risk of moving out of the firm. The proportional hazards model assumes that covariates have a multiplicative effect on a baseline hazard function. We model the baseline function as the logarithm of tenure, following the popular Weibull formulation. We estimate these duration models using the sample constructed as explained in Section 3.3.1. Note that our sample follows the structure of one observation for each year at risk of moving to entrepreneurship, required for discrete-time survival analysis (Jenkins, 1995).

Given the non-linear nature of the cloglog model, we present average marginal effects of the relevant variables on the probability of transitioning to entrepreneurship. Average marginal effects provide a straightforward interpretation of the magnitude of the effect of a variable in non-linear models. The marginal effects inform us about the impact of a one-unit increase in the explanatory variable on the probability of switching to entrepreneurship.

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[15] Hazard models are preferred over a standard linear probability model in survival analysis because they appropriately handle right-censored data that is characteristic of duration data, whereas OLS estimates of the linear probability model do not, which may lead to biased or invalid results (Box-Steffensmeier & Jones, 2004).

[16] Similar approaches have been used, for example, to study transitions into and out of entrepreneurship (e.g., Carrasco, 1999) and job-to-job transitions (Castro-Silva & Lima 2017, 2023). See Jenkins (1995) for more details on applying cloglog models for discrete-time duration models.

3.3.2.2. Direct and Indirect Effects

A key aspect of Hypotheses 2a and 2b is that the age variables for a firm's managerial workforce reduce the probability of the firm's employees transitioning to entrepreneurship, as a result of lowering the likelihood of obtaining a managerial position. Hence, being a manager acts as a mediator variable in the relationship between age on the one hand, and the transition to entrepreneurship on the other hand. We therefore calculate indirect effects of the age variables for the managerial workforce on the probability of becoming an entrepreneur running through a variable indicating if a worker occupies a top or middle managerial position. We expect the indirect effects to be negative. Hence, the age variables are expected to negatively impact the probability of employees holding a managerial position, and the lower this probability, the lower the probability of transitioning to entrepreneurship.

Figure 3.1 illustrates the indirect, direct, and total effects of age on the transition to entrepreneurship. As indicated above, we expect the indirect effects to be negative, running via a decreased likelihood of holding a managerial rank (indicated by path *a*, expected to be negative), which in turn relates to a lower probability of becoming an entrepreneur (represented by path *b*, expected to be positive). The direct effect of the managerial age variables on entrepreneurship (while controlling for the variable indicating whether a worker holds a managerial position or not) is depicted by path *c*. The total effect is given by the sum of the direct and indirect effects.

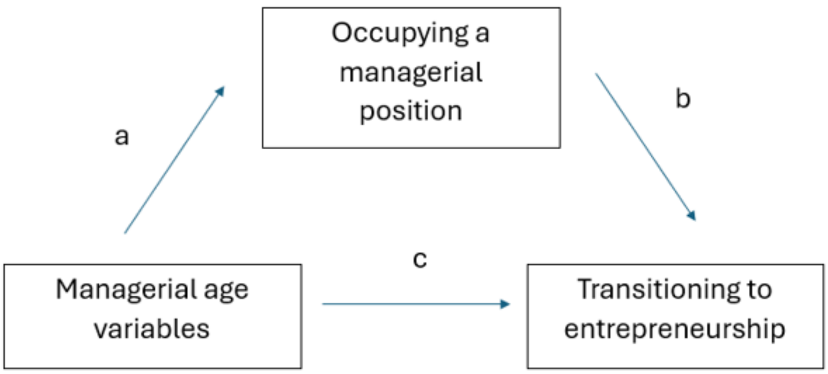

Figure 3.1 – Conceptual model depicting the direct effect (c) and indirect effect (a times b) of age on the transition to entrepreneurship.

Following Shahriar (2018), we use the Karlson-Holm-Breen (KHB) approach to calculate the effects. This approach is adequate in the present context because our dependent variable identifying transitions to entrepreneurship is binary (Karlson et al., 2012; Breen et al., 2013).

The mediator variable is a dummy variable stating if a worker is a manager (middle manager or a top manager: value 1; versus a non-manager: value 0). We calculate the indirect, direct, and total effects for our four age variables. In addition to the indirect effects, we report the proportion of the total effect (relationship between the managerial age variables and the probability of transitioning to entrepreneurship) that is due to the mediation effect, which informs us about the relative magnitude of the indirect effects (and allows us to better compare the indirect effects across variables).

3.3.2.3. Entropy Balancing

The regressions performed in this study may suffer from endogeneity associated with selection biases that impact the chances of a worker transitioning into entrepreneurship – individuals may self-select into entrepreneurship due to unobservable factors (Parker, 2005). To tackle this issue, we perform entropy balancing on our sample (Hainmueller, 2012). The entropy balancing procedure analyzes two groups of workers (the treatment group and the control group) and generates a weight for each observation, such that the two groups' distributions of a set of chosen variables are identical. These weights are included in the regressions of this study. Similar approaches have been applied in similar circumstances by, for example, Distel et al. (2019), and Fackler et al. (2022).

Entropy balancing is an alternative to other rebalancing methods such as propensity score matching. Unlike propensity score matching, entropy balancing does not require manually adjusting the weighting scheme based on the characteristics of the sample, nor to iteratively check the results of the balancing procedure (Fackler et al., 2022). Furthermore, while matching methods often remove less comparable individuals from the sample, entropy balancing keeps all observations (Hainmueller & Xu, 2013), so estimation results reflect all information available.

We theorize that joining firms with younger workforces, and particularly younger managerial workforces, will lead to a higher likelihood of reaching managerial positions, and of subsequently transitioning to entrepreneurship. Thus, workers looking for faster promotions may self-select into firms with younger workforces. We therefore perform entropy balancing between workers who join firms with managers younger than the average age of the managers in the industry (treatment group), and those who join firms with managers older than the average age of the managers in the industry (control group). The covariates we balance are age, gender and level of education. We also balance a series of individual-level variables related to the ten years prior to joining the sample: the number of years the individual worked, the number of firms the individual worked in, the logarithm of the highest wage earned, the number of years working in self-employment, the highest skill level of a job (according to ISCO-08) a worker had, and whether the worker is starting their job spell coming from non-employment. We chose these variables because workers who earn less, spend time out of work, or are unable to find a stable job are less likely to hold managerial ranks (Luijkx & Wolbers, 2009; Feng et al., 2021). Age, gender, and level of formal education should also impact the chances of holding managerial ranks (Landau, 1995; McCue, 1996; Ishida et al., 1997). We balance our variables over the first three moments, attempting to equalize the mean, variance, and skewness of these variables between the control and treatment groups, after applying the weights, as can be seen in Table 3.2.

Table 3.2 - Mean, variance and skewness of variables prior to entropy balancing procedure.

	Treatment group			Control group before entropy balancing			Control Group after entropy balancing		
	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
Age	36.02	79.6	0.5671	37.8	93.72	0.3791	36.02	79.64	0.5672
Higher education	0.2694	0.1968	1.039	0.2011	0.1606	1.492	0.2694	0.1968	1.04
Woman	0.4549	0.248	0.1812	.4526	0.2478	0.1905	0.4549	0.248	0.1812
Entered the sample from non-employment	0.244	0.1845	1.192	0.2645	0.1946	1.068	0.244	0.1845	1.192
Years at work	8.88	2.264	-1.883	8.827	2.379	-1.834	8.88	2.264	-1.883
Log (largest wage)	6.71	0.3101	0.4873	6.665	0.3026	0.6172	6.71	0.3101	0.4873
Number of firms worker was on	2.344	0.5072	1.746	2.308	0.4632	1.87	2.344	0.5072	1.747
Years as business owner	0.04042	0.1646	13.5	0.5403	0.2404	11.9	0.04045	0.1648	13.49
Maximum skill level of job occupied (1)	0.03741	0.03601	4.875	0.4534	0.4328	4.371	0.03742	0.03602	4.875
Maximum skill level of job occupied (3)	0.1116	0.09914	2.467	0.1239	0.1085	2.284	0.1116	0.09915	2.467
Maximum skill level of job occupied (4)	0.05972	0.05615	3.716	0.05605	0.05291	3.86	0.05971	0.05615	3.716

Notes: Maximum skill level of job occupied attributed following the ISCO-08 guidelines, with values going from 1 to 4, 2 being the base level. Statistics are computed considering the period of up to 10 years prior to workers joining the sample of analysis.

3.4. Results

3.4.1. Hazard Models – Management Roles (H1) and Indirect Effects of Managerial Age Variables (H2a, H2b)

Table 3.3 acts as our baseline specification and shows the results of four model specifications estimating the probability of a worker transitioning to entrepreneurship. Each model specification includes a specific managerial age variable. Model 1 focuses on the median age of top managers, and Model 2 on the median age of middle managers. We use two alternative measures of these managerial age variables in Model 3 and 4. These are: the median age at which workers reach top managerial positions (Model 3; which is an alternative measure of the age variable in Model 1); and the median age at which workers reach middle managerial positions (Model 4; which is an alternative measure of the age variable in Model 2). All models include control variables and use the weights that result from the entropy balancing procedure. The marginal effects of the managerial age variables in Table 3.3 provide the total effect of the age variables on the probability of transitioning to entrepreneurship.

For ease of interpretation, all marginal effects from Table 3.3 (and onward) are multiplied by 100. Accordingly, the reported coefficients reflect changes in the probability of the outcome measured in percentage points. Note also that our models have fewer observations than the total number available in our full sample, as shown in Table 3.1. Some firms in our sample do not register any top managers, and some do not register any middle managers, which reduces the sample size of Model 1 and Model 2, respectively. Additionally, some firms never promoted any workers to top management positions, and some never promoted any workers to middle management positions during the sample period, which reduces the sample size of Models 3 and 4, respectively.

The results in Table 3.3 show that, in all four models, the managerial age variables have significant and negative relationships with the probability of transitioning to entrepreneurship. This suggests that in firms with older managerial workforces and where managerial positions are reached at a higher age, employees are less likely to become entrepreneurs. We are, however, interested in whether these age variables indirectly reduce entrepreneurship via lowering employees' chances for obtaining managerial experience. To investigate this, we turn to Table 3.4.

Table 3.3 - Discrete-time hazard model marginal effects for transitions to entrepreneurship.

	(1)	(2)	(3)	(4)
Median age of the top managers in the firm	-0.002**			
	(0.001)			
Median age of the middle managers in the firm		-0.003***		
		(0.001)		
Firm's median worker age when reaching top manager			-0.002**	
			(0.001)	
Firm's median worker age when reaching middle manager				-0.003***
				(0.001)
Is Frustrated	-0.038	-0.030	-0.031	-0.031
	(0.034)	(0.032)	(0.032)	(0.028)
Log (Tenure)	-0.092***	-0.097***	-0.091***	-0.093***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.025***	0.022***	0.023***	0.020***
	(0.005)	(0.006)	(0.006)	(0.006)
Age (Squared)	-0.0004***	-0.0004***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.126***	-0.194***	-0.153***	-0.243***
	(0.017)	(0.027)	(0.02)	(0.035)
Woman	-0.145***	-0.119***	-0.136***	-0.111***
	(0.011)	(0.012)	(0.012)	(0.011)
High-tech	-0.027	-0.026	-0.033*	-0.043**
	(0.018)	(0.018)	(0.019)	(0.02)
Higher Education	0.155***	0.108***	0.118***	0.084***
	(0.017)	(0.016)	(0.016)	(0.015)
Worker fixed effects	0.007***	0.007***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.024***	-0.019***	-0.021***	-0.017***
	(0.005)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

The models of Table 3.4 are similar to the models as shown in Table 3.3 but add the variable denoting whether the worker is a top or middle manager (our mediator variable). Importantly, the variable denoting if a worker is a manager always shows significant and positive marginal effects. Note that this effect is path *b* in Figure 3.1. This indicates, as suggested by rank effect theory, that holding a top or middle managerial role increases the likelihood of transitioning to entrepreneurship. This provides support for Hypothesis 1.

The marginal effects of the managerial age variables in Table 3.4 (which include the mediator variable, representing path c in Figure 3.1) are less negative than those in Table 3.3 (which do not include the mediator variable). Hence, the inclusion of the mediator variable decreases the impact of the managerial age variables on the probability of becoming an entrepreneur. This suggests that there is an indirect effect running from the age variables to entrepreneurship, via holding a managerial position.

Table 3.4 - Discrete-time hazard model marginal effects for transitions to entrepreneurship, including variable "Is manager".

	(1)	(2)	(3)	(4)
Is manager	0.340***	0.202***	0.261***	0.158***
	(0.029)	(0.023)	(0.026)	(0.02)
Median age of the top managers in the firm	0.0001			
	(0.001)			
Median age of the middle managers in the firm		-0.002***		
		(0.001)		
Firm's median worker age when reaching top manager			-0.001	
			(0.001)	
Firm's median worker age when reaching middle manager				-0.002***
				(0.001)
Is Frustrated	0.019	0.007	0.014	-0.002
	(0.042)	(0.037)	(0.038)	(0.032)
Log (Tenure)	-0.099***	-0.101***	-0.095***	-0.097***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.022***	0.020***	0.021***	0.018***
	(0.005)	(0.005)	(0.005)	(0.006)
Age (Squared)	-0.0004***	-0.0003***	-0.0003***	-0.0003***
	(0.001)	(0.00001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.150***	-0.195***	-0.160***	-0.231***
	(0.017)	(0.027)	(0.02)	(0.034)
Woman	-0.134***	-0.11***	-0.127***	-0.103***
	(0.011)	(0.012)	(0.012)	(0.011)
High-tech	-0.031*	-0.030	-0.038**	-0.046**
	(0.018)	(0.018)	(0.019)	(0.02)
Higher Education	0.010	0.022	-0.004	0.016
	(0.019)	(0.017)	(0.018)	(0.016)
Worker fixed effects	0.004*	0.006***	0.005**	0.005***
	(0.003)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.024***	-0.020***	-0.020***	-0.019***
	(0.006)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* p < 0.10; ** p < 0.05; *** p < 0.01.

Before demonstrating the presence and significance of these indirect effects, we first analyze how the age variables relate to the probability of occupying a managerial position. This is path *a* as shown in Figure 3.1. Table 3.5 shows four model specifications with the probability of holding a managerial position as the dependent variable, one for each managerial age variable, as done in Tables 3.3 and 3.4.[17] All managerial age variables show a significant and negative relationship with the probability of holding a managerial position. These negative relationships are in accordance with the predictions of the rank effect.

[17] Again, all regressions use the weights resulting from entropy balancing and include the same control variables as in Tables 3.3 and 3.4.

Table 3.5 - Discrete-time hazard model marginal effects for holding a managerial position.

	(1)	(2)	(3)	(4)
Median age of the top managers in the firm	-0.508***			
	(0.009)			
Median age of the middle managers in the firm		-0.420***		
		(0.01)		
Firm's median worker age when reaching top manager			-0.392***	
			(0.016)	
Firm's median worker age when reaching middle manager				-0.282***
				(0.015)
Log (Tenure)	0.810***	0.820***	0.330***	0.425***
	(0.099)	(0.114)	(0.112)	(0.124)
Age	0.750***	0.761***	0.938***	1.047***
	(0.063)	(0.072)	(0.074)	(0.08)
Age (Squared)	-0.007***	-0.008***	-0.01***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm has both middle and top managers	2.963***	-0.067	-0.028	-3.378***
	(0.229)	(0.387)	(0.304)	(0.518)
Woman	-3.634***	-4.024***	-3.883***	-4.478***
	(0.146)	(0.167)	(0.167)	(0.183)
High-tech	-1.103***	-1.522***	-1.345***	-1.411***
	(0.273)	(0.304)	(0.315)	(0.352)
Higher Education	39.683***	38.455***	41.489***	39.714***
	(0.29)	(0.31)	(0.308)	(0.314)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

To examine whether Hypotheses 2a and 2b are supported, we compute the indirect effects for the managerial age variables using the KHB method (see Section 3.2.2). Table 3.6 presents the total effects, direct effects, and indirect effects of the managerial age variables on entrepreneurship via holding managerial positions. The indirect effects quantify by how much the managerial age variables reduce the probability of switching to entrepreneurship, via a lower likelihood of holding a managerial position. Specifically, indirect effects indicate by how much two employees who work for firms with a one-year difference in median age of managers are expected to differ in the probability of switching to entrepreneurship.

Table 3.6 shows that the indirect effects of all managerial age variables are significant and negative. The negative signs are in line with our expectations: the managerial age variables are negatively correlated to the transition to entrepreneurship in part because of a lower likelihood of the worker holding a managerial position. These significant and negative indirect effects provide support for Hypotheses 2a (median age of top managers and median age when reaching top management positions) and 2b (median age of middle managers and median age when reaching middle management positions).

Table 3.6 - Total, direct and indirect effects for transitions to entrepreneurship.

	Total Effect	Direct Effect	Indirect Effect	(Indirect effect / total effect) * 100
Median age of the top managers in the firm	-0.002**	0.0001	-0.002***	106.69
Median age of the middle managers in the firm	-0.003***	-0.002***	-0.001***	40.26
Firm's median worker age when reaching top manager	-0.002**	-0.001	-0.001***	68.16
Firm's median worker age when reaching middle manager	-0.003***	-0.002***	-0.001***	22.39

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Marginal effects multiplied by 100.

The final column of Table 3.6 reports the proportion of the total effect (relationship between the managerial age variables and the probability of transitioning to entrepreneurship) that is mediated by the mediator variable. This proportion is largest for the median age of the top managers and for the firm's median age when reaching the top management level, thus for the managerial age variables that relate to Hypothesis 2a. Interestingly, these two variables impact the transition to entrepreneurship only through the mediator variable, resulting in significant and negative indirect effects while at the same time revealing non-significant direct effects on entrepreneurship (as also shown in Table 3.4).

3.4.2. Alternative Pathways: Transition to Entrepreneurship vs. Transition to Another Firm (H3a, H3b)

We now consider whether frustration resulting from impeded or overdue promotion to managerial roles is positively related to career mobility – i.e., moving to entrepreneurship (Hypothesis 3a) or to a job in another firm (Hypothesis 3b). If frustration resulting from impeded or overdue promotion to managerial roles is positively related to entrepreneurship, we should find significant and positive marginal effects for the frustration variable in Tables 3.3 and 4. This is, however, not the case (non-significant marginal effects in Tables 3.3 and 3.4). This means we do not find evidence of later than average promotion to managerial positions serving as a push-factor leading to entrepreneurship. Hence, Hypothesis 3a is not supported by the analysis.

Table 3.7 uses the same specifications as shown in Table 3.4, but the dependent variable is the probability of switching to another firm as a wage worker. Here, the frustration variable is positively and significantly related to the probability of changing firms in all model specifications, implying that a lack of progress in one's career serves as a push factor leading workers into changing to other firms. Thus, Hypothesis 3b is supported by our results.

Table 3.7 - Discrete-time hazard model marginal effects for changing firms as a wage worker, including variable "Is manager".

	(1)	(2)	(3)	(4)
Is manager	-0.984***	-0.845***	-0.812***	-0.893***
	(0.091)	(0.1)	(0.1)	(0.104)
Median age of the top managers in the firm	-0.114***			
	(0.004)			
Median age of the middle managers in the firm		-0.097***		
		(0.004)		
Firm's median worker age when reaching top manager			-0.099***	
			(0.005)	
Firm's median worker age when reaching middle manager				-0.152***
				(0.006)
Is Frustrated	0.982***	1.262***	1.157***	1.321***
	(0.148)	(0.16)	(0.156)	(0.163)
Log (Tenure)	-6.278***	-6.685***	-6.649***	-6.949***
	(0.05)	(0.056)	(0.054)	(0.059)
Age	-0.122***	-0.112***	-0.11***	-0.142***
	(0.021)	(0.024)	(0.023)	(0.025)
Age (Squared)	-0.0004	-0.0005	-0.0005*	0.00009
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm has both middle and top managers	-1.961***	-3.186***	-1.816***	-2.955***
	(0.095)	(0.164)	(0.119)	(0.203)
Woman	-0.772***	-0.842***	-0.911***	-0.849***
	(0.055)	(0.062)	(0.061)	(0.065)
High-tech	-2.056***	-2.213***	-2.208***	-2.268***
	(0.109)	(0.123)	(0.125)	(0.138)
Higher Education	-0.572***	-0.678***	-0.403***	-0.597***
	(0.079)	(0.086)	(0.086)	(0.09)
Worker fixed effects	-0.001***	-0.001***	-0.002***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm fixed effects	-0.001***	-0.001***	-0.002***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

An important result from our estimations in Table 3.7 is that managers are less likely to move to other firms than non-managers.[18] Thus, while experience in top and middle management positions significantly increases the probability of transitioning to entrepreneurship (Table 3.4), it significantly reduces the probability of transitioning to a job in

[18] Additional estimates, shown in Table 3.A.2, in Appendix 3.A, show that top managers are significantly less likely to move firms as a wage employee than middle managers.

another firm. Hence, managers are less likely to move to other firms, but more likely to become entrepreneurs, than subordinate employees.[19]

3.4.3. Comparing Top and Middle Managers (H4a, H4b)

In this subsection, we compare top and middle managers regarding their transitions to entrepreneurship. To test Hypothesis 4a, Table 3.8 repeats the exercise of Table 3.4 but includes the variables "Is middle manager" and "Is top manager" rather than "Is manager". We observe that top managers are significantly more likely to transition to entrepreneurship than middle managers.[20] These findings provide support for Hypothesis 4a.

Table 3.8 - Discrete-time hazard model marginal effects for transitions to entrepreneurship, including variables "Is middle manager" and "Is top manager".

	(1)	(2)	(3)	(4)
Is top manager	0.447***	0.241***	0.336***	0.209***
	(0.04)	(0.037)	(0.035)	(0.034)
Is middle manager	0.25***	0.217***	0.207***	0.157***
	(0.04)	(0.028)	(0.038)	(0.025)
Median age of the top managers in the firm	0.001			
	(0.001)			
Median age of the middle managers in the firm		-0.002***		
		(0.001)		
Firm's median worker age when reaching top manager			-0.0003	
			(0.001)	
Firm's median worker age when reaching middle manager				-0.002***
				(0.001)
Is Frustrated	0.025	0.008	0.019	0.0004
	(0.043)	(0.037)	(0.039)	(0.033)
Log (Tenure)	-0.099***	-0.101***	-0.094***	-0.097***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.022***	0.020***	0.020***	0.018***
	(0.005)	(0.005)	(0.005)	(0.006)
Age (Squared)	-0.0004***	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.126***	-0.196***	-0.142***	-0.238***
	(0.017)	(0.027)	(0.02)	(0.034)
Woman	-0.133***	-0.11***	-0.127***	-0.103***
	(0.011)	(0.012)	(0.012)	(0.011)
High-tech	-0.036*	-0.030	-0.042**	-0.048**
	(0.019)	(0.018)	(0.02)	(0.02)
Higher Education	0.003	0.021	-0.006	0.013
	(0.019)	(0.017)	(0.019)	(0.017)
Worker fixed effects	0.004	0.006***	0.005**	0.005**
	(0.003)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.024***	-0.02***	-0.02***	-0.019***
	(0.006)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

[19] We also tested whether occupying a managerial position mediates the relationship between the firm-level age variables and the probability of changing firms as an employee. The results, shown in Table 3.A.3, in Appendix 3.A, indicate that this is not the case.

[20] The difference in marginal effects between "Is top manager" and "Is middle manager" is statistically significant at the 10% level for Models 1, 3 and 4. For Model 2 the difference is not significant.

To test Hypothesis 4b we focus on the difference in indirect effects between the age variables related to top managers and middle managers. Table 3.6 reveals that the indirect effect is larger in absolute (and relative) terms for the median age of the top managers than for the median age of the middle managers in the firm. Similarly, the indirect effect corresponding to the median age when reaching top management positions is larger in absolute and relative sense than for the median age when reaching middle management positions. Additional tests (not reported) reveal that these differences between top managers and middle managers are statistically significant (p-values < .01). This implies that the age of top managers, as well as the age at which top managerial positions are reached in the firm, are more decisive in reducing employees' probability of switching to entrepreneurship than the age of middle managers, and the age at which middle management positions are reached. These results provide support for Hypothesis 4b.

3.4.4. Robustness Analyses

In this subsection we report the results of various robustness checks conducted to support our results.

3.4.4.1. Managerial Experience

To understand how accumulating managerial experience impacts transitions to entrepreneurship, we performed additional regressions using the number of years spent as either a middle or top manager as a covariate, rather than the binary variable used in our main regressions[21]. Results suggest that the number of years spent as a middle manager in the sample are negatively related to transitions to entrepreneurship, while the number of years spent as a top manager in the sample are positively related to transitions to entrepreneurship. These results further support that there is a difference when it comes to how middle and top managerial experience relate to the likelihood of an entrepreneurial transition, with our findings indicating that top managerial experience may be more valuable for those who wish to become entrepreneurs.

3.4.4.2. Entropy Balancing

Following Distel et al. (2019), we run all regressions without the weights produced via entropy balancing to check if results remain consistent and are not influenced by the specific

[21] Results for these regressions are shown in Tables 3.A.4 and 3.A.5, in Appendix 3.A.

choice of characteristics used for the entropy balancing procedure[22]. We find that all the main findings are still observed and significant in the models without weights.

3.4.4.3. Individual Worker Age

We examine whether the marginal effect of holding a top or middle managerial position has a larger impact on the probability of transitions to entrepreneurship for younger workers than for older ones, which could be expected according to our theoretical framework. To do this, we add interaction terms between age (and age squared) and a variable stating if the worker is a non-manager, a middle-manager, or a top manager. The results, presented in Figure 3.2, show that the relationship between age and the probability of transitioning to entrepreneurship is different for all three cases: non-managers always have the lowest likelihood of transitioning to entrepreneurship (except for the age of 18 years old, where the differences are not significant). When comparing middle and top managers, top managers are shown to have a higher likelihood of becoming entrepreneurs, as our previous results already suggested. The difference in marginal effects between top and middle managers is significant from ages 37 to 52 (which includes the average age of both groups).

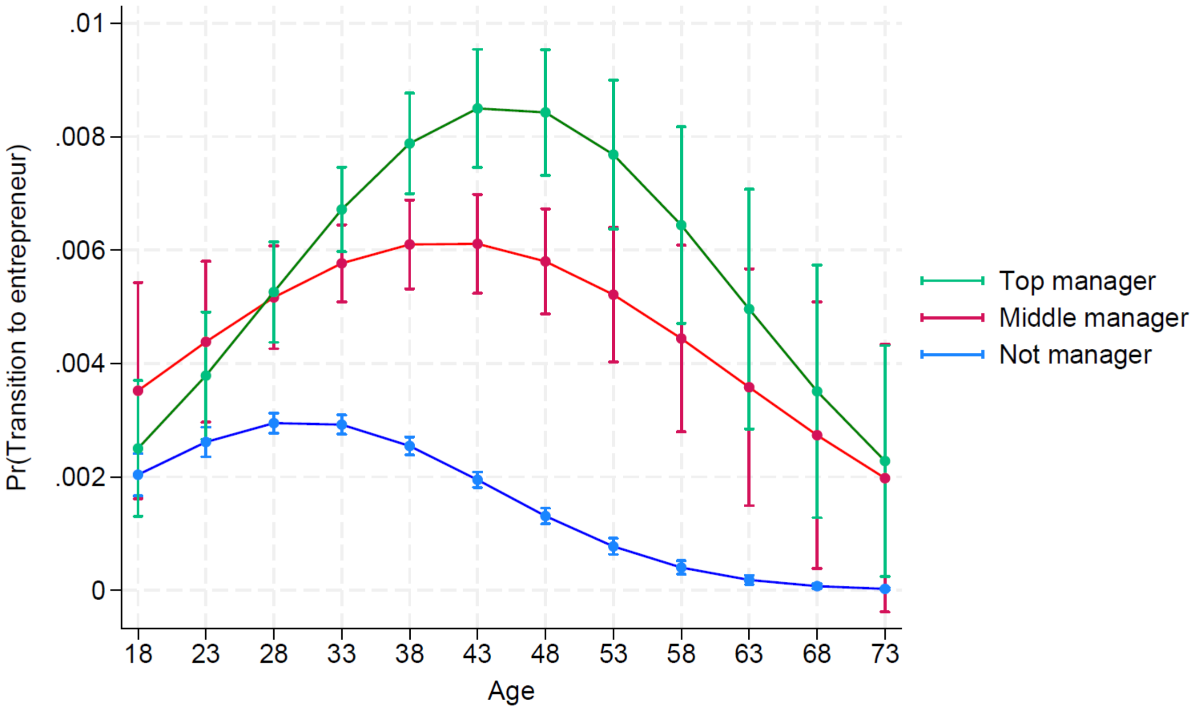

Figure 3.2 – Predicted probability of transitioning to entrepreneurship by workers' age, for workers who are top managers, middle managers and non-managers (95% confidence intervals).

[22] Results for these regressions are shown in Tables 3.A.6 and 3.A.11, in Appendix 3.A.

Looking at Figure 3.2, we can also identify the age at which the probability of transitioning to entrepreneurship peaks. For non-managers, this happens at 30.15 years old, for middle managers at 40.67 years old, and for top managers at 45 years old.[23] Hence, the relationship between holding a top and middle position and entrepreneurship is strongest for middle-aged workers. Similar to Azoulay et al. (2020)—who focus primarily on performance, and not on transitioning to entrepreneurship—our results for worker age imply that the probability of becoming an entrepreneur increases with age until a turning point, decreasing afterwards.

3.4.4.4. Age of managerial promotion

As our results have shown so far, both middle and top managers are more likely to transition to entrepreneurship. These results go in accordance with what previous literature suggests. However, we have not yet addressed whether the age at which workers reach managerial levels will impact the likelihood of entrepreneurial transitions. To analyze this, we constructed models that include the age at which workers reach middle and top managerial roles, instead of the individual worker age. The results indicate that the likelihood of transitioning to entrepreneurship, for both variables, increases initially, then reaches a threshold and decreases henceforth.[24] For the age at promotion to middle managers, the peak happens at 32.03 years old, while for the age at promotion to top managers, the peak happens at 36.91 years old. These results once more suggest that the youngest workers are not necessarily the ones who will more likely become entrepreneurs, even if they have reached managerial roles. In fact, our results also show that top managers are the ones who are more likely to become entrepreneurs, and this likelihood reaches a maximum when they are 45 years old, as shown before. Taken together, these suggest that workers in their mid-thirties to mid-forties may be the ones better suited to transition to entrepreneurship, as they have had time to accumulate relevant top-managerial experience.

3.5. Discussion

We investigate individual career paths leading to entrepreneurship and whether these career paths are influenced by the age structure of a firm's managerial workforce. Our research is motivated by rank effect theory, which argues that in companies with aging workforces, older workers fill up and hold on to most top and middle management positions, preventing

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[23] Results of the regressions that lead to Figure 3.2 and which allow us to calculate the maximum probabilities of transitioning to entrepreneurship are shown in Table 3.A.12, in Appendix 3.A.
[24] Results shown in Table 3.A.13, in Appendix 3.A.

younger workers from acquiring managerial experience that is key for entrepreneurship. Grounded on our discussion of rank effect theory and managerial capabilities, we formulate hypotheses regarding the likelihood of (top and middle) managers and non-managerial workers engaging in entrepreneurship, and the influence of the age structure of the firm's managerial ranks on the likelihood that employees will become entrepreneurs. We test these hypotheses using detailed longitudinal data for Portugal, covering business owners (including new firm founders), workers (managers and non-managers), and firms.

Rank effect theory rests on the idea that experience in managerial roles is valuable for entrepreneurship. We propose that experience in both top and middle management roles is relevant for entrepreneurship, as both top and middle managers are likely to acquire dynamic managerial capabilities that contribute to their motivation and ability to become entrepreneurs (Heaton & Teece, 2013; George et al., 2022). This claim is supported by our results, suggesting that managerial experience is key to advancing entrepreneurship, likely by providing workers with skills that make them more disposed to recognize/generate and assess opportunities, and more capable to mobilize, manage and supervise resources.

We also propose that top managers are significantly more likely to become entrepreneurs than middle managers, likely because their responsibilities, duties and external outlook are more similar to those of entrepreneurs compared to middle managers. Unlike middle managers, whose responsibilities lay more on day-to-day operations and ensuring the workflow progresses smoothly (Floyd & Wooldridge, 1997), top managers face challenges regarding long-term and complex goals, including setting the company's vision, finding and renewing resources, and ensuring stability. These top managerial tasks are closely related with those that entrepreneurs have to face. Our results confirm that top managers are more likely to become entrepreneurs than middle managers.

These results give us more insight into the type of career experiences in wage work that are most likely to lead individuals towards entrepreneurship. Policymakers seeking to promote entrepreneurship may find that middle managers seeking to take advantage of new venture opportunities could benefit from additional support such as access to funding, mentoring and networking which could help them to make a transition to entrepreneurship. Our results also illustrate that careers where workers progress relatively swiftly towards top and middle management positions represent a common pathway to entrepreneurship. We find that the likelihood of entrepreneurial transition reaches a maximum at 40.67 years old for middle managers and 45 years old for top managers.[25] This suggests that allowing promising individuals in their mid- to late-thirties to gain managerial experience is critical for fostering entrepreneurship. This corroborates similar findings by Azoulay et al. (2020) in their study of fast-growing new ventures.

We find that managers are less likely to move to other firms as wage workers, possibly because managerial human capital has a significant firm-specific component, associated with an organization's particular design and routines. Indeed, the literature indicates that firm-specific knowledge is relevant for managers (Groysberg & Lee, 2009; Campbell et al., 2014). In contrast, managerial experience specific to one firm is likely to be applicable when creating a new firm which has no pre-established structure, routines, and networks. Research on spinouts shows that startups often benefit from knowledge and routines inherited from their founders' previous employer (e.g., Phillips, 2002; Agarwal et al., 2004).

Our results also lend support to rank effect theory by showing that in firms where middle managers and, especially, top managers are older, employees are less likely to become entrepreneurs since their likelihood of reaching top and middle management positions is reduced in such firms. This finding substantiates the claim that aging managers act as a bottleneck in the promotion pipeline (Sturman, 2003). Older top managers are more detrimental than older middle managers in hampering employees' internal career progression, likely because top managers have greater decision-making power and more extensive authority on deciding promotions, particularly in small and medium sized firms. It is not clear whether older top managers inhibit entrepreneurial careers simply by holding on to their positions or whether it is (also) because of their impact on the choices regarding who gets promoted.

Interestingly, the amount of experience in middle management and top management roles shows a divergent relationship with entrepreneurship. When more time is spent working as a middle manager (while failing to reach top managerial levels), the likelihood of transitioning to entrepreneurship is lowered. This may be the result of increasing opportunity costs, or of an increasing focus on seeking an elusive promotion to top management. Previous work argues that managers are more career-driven than the average worker (Stewart, 1982; Bloom et al., 2012), which suggests that more middle managers may try to reach the top levels of the firm's hierarchy, rather than pursue entrepreneurship. Middle managers who have spent many years climbing the corporate ladder may identify strongly with the company's goals and values, and

[25] Results of the regressions which allow us to calculate the maximum probabilities of transitioning to entrepreneurship, leading to Figure 3.2, are shown in the Table 3.A.12, in Appendix 3.A.

this loyalty may discourage them from leaving the company to start their own business. Middle managers may also become more risk averse with more experience within a firm's established structures, managing existing processes and ensuring business continuity. The security and stability of their current roles might make the financial and professional risks associated with starting a new business feel too daunting.

The opposite is true for top managers, who are likely to turn to entrepreneurship even as they remain longer in their positions. It is possible that, even faced with the high opportunity costs of leaving their positions, top managers with more years of experience may be more likely and better able to encounter or recognize interesting opportunities for entrepreneurship. This may be because founding and growing a new business may provide a new and different challenge. Also experienced top managers are likely to have built up more networks and resources (including financial capabilities), making it easier to identify and assess opportunities, and raising the required resources.

We also look into what happens to workers that are impeded in their career progression. Our results indicate that those workers taking longer than average to be promoted to management are more likely to seek employment in other firms but are not more likely to become entrepreneurs. Workers with slower career progression within a firm will look for better opportunities in other established firms, rather than pursue an entrepreneurial career. This means that we do not find that workers who are unable to reach managerial ranks are pushed into entrepreneurship, as proposed by Kacperczyk & Marx (2016) and Sorensen & Sharkey (2014). This further underlines the idea that managerial experience is of key relevance for entrepreneurship.

We encourage several extensions to our analysis for future work. While we focus here on the transition to entrepreneurship, future research could incorporate and compare objective and subjective performance measures of the new businesses set up by employees who have accumulated managerial experience at different ages, as well as those businesses set up by non-managerial employees. It would also be worthwhile to compare the performance of those who transition to entrepreneurship soon after becoming manager versus those who transition after having acquired managerial experience for a longer period. Furthermore, it would be interesting to examine the type of opportunities pursued by entrepreneurs with different organizational backgrounds, as possibly a quick transition towards entrepreneurship is triggered mainly by exposure to a valuable entrepreneurial opportunity, while a longer transition may allow for the accumulation of relevant skills and resources.

3.6. Conclusion

This paper has looked at how corporate careers unfold over time towards entrepreneurship, focusing on whether holding top and middle managerial ranks is a steppingstone towards entrepreneurship. We examine how the age characteristics of a firm's top and middle managerial workforce affect their employees' entrepreneurial prospects, using longitudinal micro data matching firms, workers and business founders. While younger people are more likely to possess the time, energy, creativity and risk tolerance needed for an entrepreneurial career, they often require skills that can only be acquired in wage employment before they can pursue entrepreneurship. This study is the first to link the age of a firm's managerial workforce to the probability of the firm's employees becoming entrepreneurs.

Workforce aging is a growing concern in most developed societies. Rank effect theory (Liang et al., 2018) proposes that entrepreneurship should slow down in aging societies because older workers will tend to hold on to the managerial ranks that provide crucial skills for would-be entrepreneurs (a phenomenon dubbed the rank effect). Our findings support this theory and demonstrate that in firms with older top and middle management ranks, workers are less likely to reach managerial positions, and that this reduces their likelihood of becoming an entrepreneur. This has potential negative impacts on innovation, job creation, and economic growth in aging societies as young workers – more likely to possess the required vitality and risk-taking disposition for entrepreneurship – are less likely to become entrepreneurs. Moreover, we find that top managers are more likely to become entrepreneurs than middle managers, suggesting that the experience obtained at the very top of a firm's ladder may be better suited for future business-owners.

We contribute to the literature on age and entrepreneurship by establishing the relevance of the age of a firm's managerial workforce for the firm's likelihood of spawning entrepreneurs. In particular, we show that holding a managerial position represents an indirect channel through which workforce aging affects entrepreneurship. We extend rank effect theory by showing that it especially holds when firms have older managers (in particular, older top managers). We add to the literature on career paths leading to entrepreneurship (Kim et al., 2006; Burton et al., 2016) and to the research on the relationship between dynamic managerial capabilities and entrepreneurship (Staniewski, 2016; George et al., 2022) by showing that early access in one's career to such key management positions is a vital path leading to entrepreneurship.

While the skills and qualities required for managerial and entrepreneurial careers are often seen as different, our analysis suggests that holding top and middle management ranks is an important steppingstone for those individuals whose career path progresses from wage employment to entrepreneurship. By verifying this relationship between managerial experience and entrepreneurship at the firm level, we are able to claim that a firm's propensity to spawn entrepreneurs (i.e., generate spinouts) likely depends not just on its ability to generate new ideas and product lines, but is also related with the age structure of its managerial workforce. Moreover, firms' organizational forms and structures, which determine the numbers and functions of top and middle managers, are also likely to play a role.

It should be noted that, while more entrepreneurship among the young and middle-aged is certainly desirable to promote the economic growth of countries and regions through the development of new products and processes (Frosch, 2011), it may not be in the interest of incumbent firms that their more valuable employees transition into entrepreneurship. Typically, firms seek ways to keep their staff from leaving to start new businesses that potentially might exploit opportunities and use knowledge developed while employed (Marx, 2011; Can & Fossen, 2022).

3.A. Appendix

Table 3.A.1 – High dimensional fixed-effects model coefficients for wage.

	(1)
Age	16.65***
	(0.380)
Age (squared)	-0.18***
	(0.003)
Tenure	5.75***
	(0.127)
Tenure (squared)	0.58***
	(0.004)
Woman	-43.27***
	(3.05)
Higher Education	5.299***
	(1.268)
Log (Firm Size)	49.63***
	(0.8)
Firm Sales (Log, in euro)	1.12***
	(0.908)
Observations	34139891

Notes: Regressions also control for year dummies, region dummies, industry dummies and job level of the worker. Clustered standard errors in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.2 - Discrete-time hazard model marginal effects for changing firms as a wage worker, including variables "Is middle manager" and "Is top manager".

	(1)	(2)	(3)	(4)
Is top manager	-1.255***	-0.831***	-1.083***	-0.948***
	(0.104)	(0.134)	(0.114)	(0.134)
Is middle manager	-0.566***	-0.844***	-0.398***	-0.833***
	(0.123)	(0.115)	(0.133)	(0.122)
Median age of the top managers in the firm	-0.116***			
	(0.004)			
Median age of the middle managers in the firm		-0.097***		
		(0.004)		
Firm's median worker age when reaching top manager			-0.1***	
			(0.005)	
Firm's median worker age when reaching middle manager				-0.152***
				(0.006)
Is Frustrated	0.965***	1.263***	1.142***	1.317***
	(0.147)	(0.16)	(0.155)	(0.163)
Log (Tenure)	-6.278***	-6.685***	-6.651***	-6.95***
	(0.05)	(0.056)	(0.054)	(0.059)
Age	-0.122***	-0.112***	-0.109***	-0.142***
	(0.021)	(0.024)	(0.023)	(0.025)
Age (Squared)	-0.0004	-0.0005	-0.0006*	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm has both middle and top managers	-2.011***	-3.186***	-1.867***	-2.949***
	(0.096)	(0.164)	(0.12)	(0.204)
Woman	-0.774***	-0.842***	-0.912***	-0.85***
	(0.055)	(0.062)	(0.061)	(0.065)
High-tech	-2.046***	-2.213***	-2.197***	-2.267***
	(0.109)	(0.123)	(0.125)	(0.138)
Higher Education	-0.556***	-0.679***	-0.388***	-0.594***
	(0.079)	(0.086)	(0.086)	(0.09)
Worker fixed effects	-0.001***	-0.001***	-0.002***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm fixed effects	-0.001***	-0.001***	-0.002***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	1150363	931419	979940	856539

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.A.3 - Total, Direct and Indirect Effects for changing firms as a wage worker.

	Total Effect	Direct Effect	Indirect Effect	(Indirect effect / total effect) * 100
Median age of the top managers in the firm	-0.109***	-0.114***	0.005***	-4.26
Median age of the middle managers in the firm	-0.094***	-0.097***	0.003***	-3.59
Firm's median worker age when reaching top manager	-0.096***	-0.099***	0.003***	-3.85
Firm's median worker age when reaching middle manager	-0.149***	-0.152***	0.003***	-2.19

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), number of years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Marginal effects multiplied by 100.
*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.4 – Discrete-time hazard model marginal effects for transitions to entrepreneurship, using years as top manager in sample.

	(1)	(2)	(3)	(4)
Years as top manager in sample	0.057***	0.047***	0.051***	0.044***
	(0.012)	(0.01)	(0.011)	(0.009)
Median age of the top managers in the firm	-0.002			
	(0.003)			
Median age of the middle managers in the firm		-0.009***		
		(0.003)		
Firm's median worker age when reaching top manager			0.002	
			(0.003)	
Firm's median worker age when reaching middle manager				-0.005*
				(0.003)
Is Frustrated	0.237	0.204	0.311	0.233
	(0.442)	(0.336)	(0.394)	(0.309)
Log (Tenure)	-0.23***	-0.169***	-0.202***	-0.171***
	(0.043)	(0.038)	(0.04)	(0.033)
Age	0.111***	0.070***	0.071***	0.037*
	(0.024)	(0.022)	(0.022)	(0.02)
Age (Squared)	-0.001***	-0.001***	-0.001***	-0.0004*
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Firm has both middle and top managers	-0.286***	-0.364***	-0.196***	-0.453***
	(0.06)	(0.085)	(0.059)	(0.094)
Woman	-0.385***	-0.267***	-0.377***	-0.256***
	(0.041)	(0.04)	(0.04)	(0.038)
High-tech	-0.335***	-0.256***	-0.282***	-0.292***
	(0.083)	(0.077)	(0.078)	(0.08)
Higher Education	-0.306***	-0.127**	-0.298***	-0.119**
	(0.058)	(0.051)	(0.057)	(0.049)
Worker fixed effects	0.011*	0.015***	0.014**	0.010**
	(0.007)	(0.006)	(0.006)	(0.005)
Firm fixed effects	-0.039**	-0.025	-0.025*	-0.048
	(0.015)	(0.017)	(0.013)	(0.036)
Observations	194314	165677	181042	163051

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.5 – Discrete-time hazard model marginal effects for transitions to entrepreneurship, using years as middle manager in sample.

	(1)	(2)	(3)	(4)
Years as middle manager in sample	-0.055***	-0.044***	-0.045***	-0.046***
	(0.016)	(0.012)	(0.014)	(0.011)
Median age of the top managers in the firm	-0.002			
	(0.003)			
Median age of the middle managers in the firm		-0.009***		
		(0.003)		
Firm’s median worker age when reaching top manager			0.001	
			(0.003)	
Firm’s median worker age when reaching middle manager				-0.006*
				(0.003)
Is Frustrated	0.250	0.217	0.298	0.266
	(0.449)	(0.342)	(0.39)	(0.324)
Log (Tenure)	-0.093**	-0.060	-0.081**	-0.062*
	(0.036)	(0.038)	(0.035)	(0.033)
Age	0.113***	0.072***	0.074***	0.04**
	(0.024)	(0.022)	(0.022)	(0.02)
Age (Squared)	-0.001***	-0.001***	-0.001***	-0-0005*
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Firm has both middle and top managers	-0.296***	-0.372***	-0.208***	-0.465***
	(0.061)	(0.086)	(0.059)	(0.095)
Woman	-0.385***	-0.267***	-0.378***	-0.257***
	(0.041)	(0.04)	(0.04)	(0.037)
High-tech	-0.340***	-0.258***	-0.284***	-0.297***
	(0.083)	(0.077)	(0.078)	(0.081)
Higher Education	-0.284***	-0.108**	-0.273***	-0.100**
	(0.056)	(0.049)	(0.055)	(0.047)
Worker fixed effects	0.012*	0.016***	0.015**	0.011**
	(0.007)	(0.006)	(0.006)	(0.005)
Firm fixed effects	-0.038**	-0.024	-0.024*	-0.047
	(0.015)	(0.018)	(0.013)	(0.036)
Observations	194314	165677	181042	163051

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.6 – Discrete-time hazard model marginal effects for transitions to entrepreneurship, without weights from entropy balancing.

	(1)	(2)	(3)	(4)
Median age of the top managers in the firm	-0.002***			
	(0.001)			
Median age of the middle managers in the firm		-0.003***		
		(0.001)		
Firm's median worker age when reaching top manager			-0.001*	
			(0.001)	
Firm's median worker age when reaching middle manager				-0.003***
				(0.001)
Is Frustrated	-0.029	-0.031	-0.028	-0.028
	(0.033)	(0.03)	(0.031)	(0.027)
Log (Tenure)	-0.091***	-0.093***	-0.091***	-0.092***
	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.026***	0.024***	0.024***	0.021***
	(0.005)	(0.005)	(0.005)	(0.005)
Age (Squared)	-0.0004***	-0.0004***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.123***	-0.200***	-0.148***	-0.250***
	(0.015)	(0.026)	(0.019)	(0.033)
Woman	-0.153***	-0.129***	-0.145***	-0.123***
	(0.01)	(0.011)	(0.011)	(0.011)
High-tech	-0.021	-0.018	-0.023	-0.034*
	(0.017)	(0.017)	(0.017)	(0.018)
Higher Education	0.147***	0.109***	0.117***	0.088***
	(0.015)	(0.014)	(0.015)	(0.014)
Worker fixed effects	0.008***	0.008***	0.008***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.025***	-0.019***	-0.025***	-0.017***
	(0.004)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.7 - Discrete-time hazard model marginal effects for transitions to entrepreneurship, including variable “Is manager”, without weights from entropy balancing.

	(1)	(2)	(3)	(4)
Is manager	0.357***	0.203***	0.277***	0.154***
	(0.028)	(0.021)	(0.025)	(0.019)
Median age of the top managers in the firm	-0.0004			
	(0.001)			
Median age of the middle managers in the firm		-0.002***		
		(0.001)		
Firm’s median worker age when reaching top manager			-0.0004	
			(0.001)	
Firm’s median worker age when reaching middle manager				-0.003***
				(0.001)
Is Frustrated	0.028	0.004	0.017	-0.001
	(0.04)	(0.034)	(0.036)	(0.031)
Log (Tenure)	-0.098***	-0.098***	-0.094***	-0.096***
	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.024***	0.022***	0.022***	0.019***
	(0.005)	(0.005)	(0.005)	(0.005)
Age (Squared)	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.148***	-0.199***	-0.155***	-0.237***
	(0.016)	(0.026)	(0.019)	(0.032)
Woman	-0.142***	-0.120***	-0.135***	-0.116***
	(0.01)	(0.011)	(0.011)	(0.011)
High-tech	-0.027	-0.023	-0.030*	-0.038**
	(0.017)	(0.017)	(0.018)	(0.018)
Higher Education	-0.012	0.018	-0.012	0.018
	(0.017)	(0.016)	(0.017)	(0.016)
Worker fixed effects	0.006**	0.007***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.027***	-0.020***	-0.024***	-0.018***
	(0.004)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.8 - Discrete-time hazard model marginal effects for holding a managerial position, without weights from entropy balancing.

	(1)	(2)	(3)	(4)
Median age of the top managers in the firm	-0.431***			
	(0.008)			
Median age of the middle managers in the firm		-0.375***		
		(0.009)		
Firm's median worker age when reaching top manager			-0.338***	
			(0.013)	
Firm's median worker age when reaching middle manager				-0.205***
				(0.013)
Log (Tenure)	0.808***	0.944***	0.331***	0.416***
	(0.088)	(0.102)	(0.099)	(0.11)
Age	0.619***	0.651***	0.785***	0.913***
	(0.058)	(0.066)	(0.067)	(0.073)
Age (Squared)	-0.007***	-0.007***	-0.009***	-0.01***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm has both middle and top managers	2.616***	-0.627*	-0.245	-3.781***
	(0.205)	(0.352)	(0.268)	(0.469)
Woman	-3.74***	-4.19***	-4.058***	-4.628***
	(0.129)	(0.149)	(0.146)	(0.162)
High-tech	-0.727***	-1.042***	-0.896***	-0.857***
	(0.237)	(0.26)	(0.271)	(0.298)
Higher Education	41.976***	40.443***	43.696***	41.937***
	(0.28)	(0.296)	(0.293)	(0.3)
Observations	1150363	931419	979940	856539

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.9 - Total, direct and indirect effects for transitions to entrepreneurship, without weights from entropy balancing.

	Total Effect	Direct Effect	Indirect Effect	(Indirect effect / total effect) * 100
Median age of the top managers in the firm	-0.002***	-0.0004	-0.002***	83.01
Median age of the middle managers in the firm	-0.003***	-0.002***	-0.001***	38.56
Firm's median worker age when reaching top manager	-0.001*	-0.0004	-0.001***	72.60
Firm's median worker age when reaching middle manager	-0.003***	-0.003***	-0.001***	18.49

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Marginal effects multiplied by 100.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.10 - Discrete-time hazard model marginal effects for changing firms as a wage worker, including variable "Is manager", without weights from entropy balancing.

	(1)	(2)	(3)	(4)
Is manager	-1.060***	-0.807***	-0.911***	-0.969***
	(0.083)	(0.093)	(0.091)	(0.095)
Median age of the top managers in the firm	-0.117***			
	(0.004)			
Median age of the middle managers in the firm		-0.094***		
		(0.004)		
Firm's median worker age when reaching top manager			-0.102***	
			(0.005)	
Firm's median worker age when reaching middle manager				-0.154***
				(0.005)
Is Frustrated	1.098***	1.38***	1.234***	1.423***
	(0.139)	(0.151)	(0.146)	(0.153)
Log (Tenure)	-6.243***	-6.688***	-6.617***	-6.936***
	(0.046)	(0.052)	(0.05)	(0.055)
Age	-0.102***	-0.086***	-0.089***	-0.110***
	(0.02)	(0.023)	(0.022)	(0.024)
Age (Squared)	-0.001***	-0.001***	-0.001***	-0.001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Firm has both middle and top managers	-2.129***	-3.335***	-1.956***	-2.966***
	(0.091)	(0.158)	(0.114)	(0.193)
Woman	-0.755***	-0.808***	-0.890***	-0.816***
	(0.052)	(0.058)	(0.057)	(0.061)
High-tech	-2.163***	-2.335***	-2.338***	-2.4***
	(0.104)	(0.117)	(0.118)	(0.131)
Higher Education	-0.482***	-0.572***	-0.28***	-0.495***
	(0.072)	(0.08)	(0.079)	(0.083)
Worker fixed effects	-1.332***	-1.362***	-1.688***	-1.361***
	(0.092)	(0.103)	(0.12)	(0.106)
Firm fixed effects	-1.059***	-1.059***	-2.431***	-1.061***
	(0.112)	(0.092)	(0.142)	(0.095)
Observations	1150363	931419	979940	856539

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 3.A.11 - Discrete-time hazard model marginal effects for transitions to entrepreneurship, including variables “Is middle manager” and “Is top manager”, without weights from entropy balancing.

	(1)	(2)	(3)	(4)
Is top manager	0.481***	0.251***	0.362***	0.202***
	(0.039)	(0.035)	(0.034)	(0.031)
Is middle manager	0.252***	0.217***	0.22***	0.153***
	(0.037)	(0.026)	(0.036)	(0.024)
Median age of the top managers in the firm	0.0003			
	(0.001)			
Median age of the middle managers in the firm		-0.002***		
		(0.001)		
Firm’s median worker age when reaching top manager			-0.0002	
			(0.001)	
Firm’s median worker age when reaching middle manager				-0.003***
				(0.001)
Is Frustrated	0.036	0.006	0.022	0.002
	(0.041)	(0.035)	(0.037)	(0.032)
Log (Tenure)	-0.099***	-0.098***	-0.094***	-0.096***
	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.023***	0.022***	0.022***	0.019***
	(0.005)	(0.005)	(0.005)	(0.005)
Age (Squared)	-0.0004***	-0.0004***	-0.0004***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Firm has both middle and top managers	-0.120***	-0.202***	-0.136***	-0.243***
	(0.015)	(0.026)	(0.018)	(0.033)
Woman	-0.141***	-0.119***	-0.135***	-0.115***
	(0.01)	(0.011)	(0.011)	(0.011)
High-tech	-0.031*	-0.024	-0.033*	-0.039**
	(0.017)	(0.017)	(0.018)	(0.018)
Higher Education	-0.021	0.016	-0.018	0.015
	(0.017)	(0.016)	(0.017)	(0.016)
Worker fixed effects	0.005*	0.007***	0.006**	0.006***
	(0.003)	(0.002)	(0.002)	(0.002)
Firm fixed effects	-0.027***	-0.020***	-0.024***	-0.019***
	(0.004)	(0.003)	(0.006)	(0.003)
Observations	1150363	931419	979940	856539

Notes: Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.A.12 - Discrete-time hazard model marginal effects for transitions to entrepreneurship, for workers who are top managers, middle managers and non-managers.

	(1)
Is top manager	-0.022
	(0.859)
Is middle manager	1.277
	(0.994)
Age	0.156***
	(0.022)
Age (Squared)	-0.003***
	(0.0003)
Is top manager times Age	-0.003
	(0.0438)
Is middle manager times Age	-0.067
	(0.0514)
Is top manager times Age squared	0.001
	(0.001)
Is middle manager times Age squared	0.001**
	(0.001)
Is Frustrated	0.049
	(0.132)
Log (Tenure)	-0.320***
	(0.031)
Firm has both middle and top managers	-0.426***
	(0.043)
Woman	-0.495***
	(0.039)
High-tech	-0.038
	(0.052)
Higher Education	-0.003
	(0.059)
Worker fixed effects	0.008
	(0.009)
Firm fixed effects	-0.083***
	(0.015)
Observations	1248652

Notes: This regression includes the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3.A.13 – Discrete-time hazard model coefficients for transitions to entrepreneurship, considering age when reaching middle manager and age when reaching top manager.

	(1)	(2)
Age when reaching top manager	0.060*	
	(0.031)	
Age when reaching top manager (squared)	-0.001**	
	(0)	
Age when reaching middle manager		0.057*
		(0.03)
Age when reaching middle manager (squared)		-0.001**
		(0)
Is Frustrated	-0.062	-0.128***
	(0.049)	(0.048)
Log (Tenure)		0.409
		(0.48)
Firm has both middle and top managers	-0.267***	-0.517***
	(0.07)	(0.093)
Woman	-0.559***	-0.28***
	(0.066)	(0.055)
High-tech	-0.249***	-0.199**
	(0.087)	(0.099)
Higher Education	-0.477***	-0.152**
	(0.068)	(0.061)
Worker fixed effects	0.014*	0.030
	(0.008)	(0.028)
Firm fixed effects	-0.048***	-0.084
	(0.018)	(0.057)
Observations	120594	94419

Notes: All regressions include the weights obtained via entropy balancing. Regressions also control for year dummies, region, logarithm of firm size (number of workers), years worked in the 10 years prior to joining the sample, number of firms the individual worked in the 10 years prior to joining the sample, years working as self-employed in the 10 years prior to joining the sample, highest skill level of a job (according to ISCO-08) a worker had in the 10 years prior to joining the sample, and if the worker is starting this job spell coming from non-employment. Clustered standard errors in parentheses. Marginal effects multiplied by 100. Marginal effects of worker and firm fixed effects multiplied by 100000.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Chapter 4

From Experience to Implementation: How Founders' and Employees' Backgrounds Drive Startup Outcomes

4.1. Introduction

The decision to transition into entrepreneurship and the subsequent performance of startups are central topics in entrepreneurial research. Among several factors influencing these phenomena, the "small firm effect" and the role of managerial experience have been the focus of past studies. The small firm effect, as documented in studies such as Parker (2009), Elfenbein et al. (2010) and Kacperczyk and Marx (2016), posits that employees of smaller firms are more likely to transition into entrepreneurship compared to their counterparts in larger firms. This effect has been attributed to, among other factors, the diverse skill acquisition, greater autonomy, and broader exposure to different sides of business operations, typically more easily attainable in smaller than in larger firms (Lazear, 2005; Sørensen, 2007). Managerial experience has also been pointed out as a key factor behind entrepreneurial transitions (Dobrev and Barnett, 2005; Kim et al., 2006), with studies emphasizing its importance for decision-making, strategic planning, and navigating the complexities of running a business (Bosma et al., 2004; Dobrev & Barnett, 2005).

The growing body of literature on both the importance of managerial experience, and particularly on the small firm effect, is often concerned with the likelihood of entrepreneurial transitions. However, less attention has been devoted to factors impacting startup performance, particularly in relation to founder characteristics regarding firm size of origin, and if managerial experience plays a role in this relationship. In our study, we examine whether startups founded by individuals with experience in small firms perform better than those founded by individuals from larger firms and whether founders with managerial experience lead startups with better performance. Analysing firm performance is critical in entrepreneurship research, as it allows researchers to understand the ability of startups to achieve growth, profitability, and long-term survival. Past research has shown that founder characteristics may significantly impact startup performance (Bosma et al., 2004), as founders with higher human capital are more likely to lead high-performing firms (Colombo & Grilli, 2005).

Moreover, the performance of firms is not only influenced by characteristics of their founders, but may also be impacted by a firms' employees (Rauch et al. 2005; Koch et al., 2013). However, as pinpointed by Koch et al. (2013) and Rocha et al. (2018), most studies analyzing the relevance of employees' characteristics for firm performance focus on incumbent firms, and not on startups. We investigate how the characteristics of a startup's employees influence its performance, focusing on the size of the firms they previously worked at, and whether they have managerial experience.

We propose that the impact of founders' and employees' prior experiences on startup performance will vary depending on the startup's age. Small firm experience of founders and employees is likely more relevant in early stages of the startup's age, when liability of newness is particularly high, whereas large firm experience is likely more relevant in later stages, when the startup matures.

In this study we use correlated random effects models to examine how the combination of past firm size and managerial experience of startups' founders and employees shapes entrepreneurial success. We analyse firms created from 2010 to 2019, following them until either until 2019 (the last year of data available to us), or until the firm is no longer in our dataset. The data come from *Quadros de Pessoal* and *Sistema de Contas Integradas de Empresas*, two rich Portuguese datasets with extensive information at the firm and worker levels.

To the best of our knowledge, besides the lack of past research on the impact that startups' workforces have on performance, past studies have not addressed if startups that hire employees with past managerial experience will have better performances than those that do not. Furthermore, while past research has analysed if startups' founders' past firm size impacts performance, this has not been the case for workforces of startups. As the characteristics of firm's employees can have a strong impact on performance (Rynes et al. 1997; Rauch et al. 2005), in this study, we aim to understand how workers hired in the early stages of firms' lives affect their outcomes, filling the gap in current literature.

Moreover, by analyzing how managerial experience and prior firm size influence performance at different stages of a startup's lifecycle, this research aims to uncover potential heterogeneity in their effects over time, providing insight into what different types of founders' and employees' prior experience are most useful in different stages of a startup's lifecycle, as different skillsets may prove valuable in different periods of firms' lives.

Our results indicate that firms whose founders had past managerial experience outperform those whose founders did not. Similarly, our findings illustrate that a higher share of employees with managerial experience is linked with increased startup performance. Moreover, we find that, during the early years of a startup's life, those whose founders had past experience in small firms are the better performing, but that this shifts in later years, when startups created by individuals with large firm experience excel. We also find that startups whose founders had prior managerial and large firm experiences, after the initial years of their lives, are the better performing of all the startups in our sample. Lastly, we show that a higher share of employees with small firm experience lead to better startup performance at the beginning of a startup's life, but that, when the startup matures, a higher share of employees with large firm experience, particularly when paired with past managerial experience, is linked with better performance.

The rest of the paper is structured as follows. In Section 4.2 we discuss prior past research on the topics connected with our study. In Section 4.3 we present and develop the hypotheses we address in this study. Section 4.4 introduces the datasets and methodologies that will be used to conduct our analyses, as well as descriptive statistics of our sample. In Section 4.5 we show the results of the models we construct, addressing the hypotheses we presented in Section 4.3, as well as performing robustness analyses. In Section 4.6 we discuss our results. Lastly, Section 4.7 concludes the paper with final remarks.

4.2. Background

4.2.1. Small Firm Effect

The relationship between firm size and entrepreneurship has been a topic of interest in past research on entrepreneurial transitions. One theory discussed in this domain is the "small firm effect". This theory indicates that individuals employed in smaller firms are more likely to become entrepreneurs when compared to their counterparts in larger firms.

Parker (2009) offers a foundational study on this theory. The author states that smaller firms often have less structured hierarchies, with less-formalized job levels, in which workers engage in a broader range of tasks than in larger firms. As such, smaller firms provide an environment in which employees may face unique opportunities to develop varied skills and autonomy. This larger exposure to different tasks within the job fosters workers in smaller firms with diverse skillsets and a more comprehensive understanding of business operations, which may be critical when individuals transition into entrepreneurship.

Dobrev and Barnett (2005) delve further into this phenomenon, pinpointing that smaller firms often facilitate obtaining broader outside networks, which can act as catalysts for possible future entrepreneurial ventures.

Parker (2006) suggests that small firms may attract less risk-averse workers, and that these same workers may be more inclined to transition into entrepreneurship, if an appropriate opportunity arises. Workers who prefer less bureaucratic environments, that provide them with more job autonomy, may also have a stronger preference for working in smaller firms, and may also be more driven towards the greater independence that becoming an entrepreneur would provide (Hamilton, 2000; Benz & Frey, 2008; Elfenbain et al., 2010).

The notion of opportunity cost has also been pinpointed as being closely related to the small firm effect. In larger firms, employees often face higher opportunity costs related to leaving the firms, as they have, on average, more stable and well-compensated positions (Troske, 1999). These higher costs would make entrepreneurial transitions less likely for workers in larger firms. On the other hand, employees in smaller firms, who often face lower financial and professional opportunity costs, may perceive entrepreneurship as a more viable option (Brown & Medoff, 1989).

Lastly, Kacperczyk and Marx (2016) theorize that the small firm effect may happen due to a lack of career progression opportunities within small firms, which could push workers into entrepreneurship. This push factor suggests that the small firm effect may take place not due to an accumulation of skills that would be beneficial for workers who want to become entrepreneurs, but rather because workers who are not progressing in their careers while working in small firms may look for better opportunities within entrepreneurship.

4.2.2. Managerial Experience

Past entrepreneurial research states that knowledge acquired while employed can play a significant role in fostering the success of entrepreneurs (Agarwal et al., 2004; Dobrev & Barnett, 2005). Managerial experience, in particular, may be crucial in shaping entrepreneurial transitions, and has garnered substantial attention in past research (Kim et al., 2006).

Managerial roles often require individuals to develop expertise in decision-making, resource acquisition and allocation, and team-management skills. Crucially, all these skills are also critical for entrepreneurs. Due to this, Lazear (2005) suggests that managerial experience provides employees with the human capital and strategic knowledge needed to successfully launch new firms. Moreover, besides the skillset obtained, managers are also more likely to have built professional networks that can provide access to funding, partnerships, and market opportunities. (Stuart & Sorenson, 2003).

Liang et al. (2018) also propose that managerial experience is key to entrepreneurship. The authors suggest that in older societies, in which workers reach managerial positions only later in their lives (when they are less prone to become business owners), entrepreneurial rates will decrease as a result of these delays in career progression.

4.2.3. Performance

Past studies on the importance of managerial experience in entrepreneurship, and particularly on the small firm effect, have often focused on the likelihood of entrepreneurial transitions. However, past research has also shown that these characteristics of firm founders may impact the subsequent performance of the startups they create.

Regarding the small firm effect, the ability-driven arguments that are at its core – that workers in smaller firms obtain a diverse set of skills which allow them to better identify and exploit potential entrepreneurial opportunities – would explain why more entrepreneurs come from smaller firms, but could also suggest that firms created by founders coming from smaller firms would tend to outperform their counterparts founded by those with experience in larger firms. Elfenbein et al.'s (2010) findings go in accordance with this. Analysing firms created by engineers and scientists, the authors highlight that those who worked at smaller firms were more prone to become entrepreneurs, and that the new firms started by individuals with small firm experience tended to perform better than those started by individuals coming from larger firms.

The role of managerial experience in shaping startup performance has received considerable attention in the literature. Prior research suggests that such experience equips individuals with a broad set of skills, ranging from decision-making and team leadership to resource acquisition and allocation, which are critical for entrepreneurial success (Lazear, 2005). This perspective not only helps explain why individuals with managerial backgrounds are more likely to transition into entrepreneurship, but also supports the idea that they are better positioned to succeed once they do. These insights align closely with Lazear's (2005) "Jack-of-all-trades" hypothesis, which argues that individuals with varied skillsets are more likely to succeed as entrepreneurs. Founders with managerial experience, having developed generalist capabilities through on-the-job learning, may thus be closer to this ideal notion of an entrepreneur. As a result, their startups may benefit from a stronger foundation for growth and innovation.

Also emphasizing the importance of managerial experience, Heaton and Teece (2013) argue that dynamic managerial capabilities are critical for startups to identify opportunities and make effective investment decisions, enabling startup founders to coordinate and supervise key functions, therefore enhancing their likelihood of entrepreneurial success.

Lastly, even though the majority of past research on firm performance focuses on the characteristics of firms' founders (Bates 1990; Cooper et al. 1994), past studies also suggest that the characteristics of a firm's employees will impact performance (Rauch et al. 2005). Workers bring knowledge and skills to firms that contribute to its goals, and, as such, firms hire employees based on their work experience, since they expect experienced and skilled employees to perform better (Rynes et al. 1997).

Bender et al. (2018) show that firms with more skilled employees have higher productivity. Similarly, Maliranta & Nurmi (2019) find that firms whose employees had experience in high-productivity firms were more productive and had higher survival chances than firms without employees with such experience.

Analysing startups, Koch et al. (2013) state that the employees hired during the early stages of startup development have a strong impact on the early growth of the startup, as their employees' skillsets allow firms to benefit from unique experiences and networks.

4.3. Hypotheses

We now present the hypotheses we will be testing in this study, based on the literature review shown in section 4.2.

Starting with the impact that founders' managerial experience will have on startup performance, past studies have emphasized that managerial experience allows workers to develop skills that are crucial for entrepreneurship, such as enhanced decision-making, strategic planning and resource management (Bosma et al., 2004; Elfenbein et al., 2010). Given this, we present our first hypothesis:

Hypothesis 1: Startups created by founders with managerial experience will perform better than those created by founders without managerial experience.

When it comes to the impact on performance of the size of the firms where startup founders previously worked at, we argue that it may vary over the lifecycle of the startup. The early years of startups' lives are marked by high uncertainty due to financial constraints, operational inefficiencies, and the need to establish a viable business model (Aldrich & Fiol, 1994). Founders with experience in small firms may be better suited to navigate in such scenarios, as they may have had to take on multiple roles and responsibilities in their previous firms, fostering a diverse skillset that is crucial to handle the initial turmoil associated with young firms (Parker, 2009). However, as startups age, initial uncertainty diminishes, and firms transition toward more structured operations, adapting standard operating procedures and developing stricter organizational hierarchies (Greiner, 1972; Churchill & Lewis, 1983). At this stage, the adapting skills that were beneficial in the early years may become less relevant, and the skillset developed by workers with large firm experience may become more beneficial. Taking this into account, we formulate our second and third hypotheses:

Hypothesis 2: Startups created by founders with small firm experience will perform better, in the early years of a startup's life, than those created by founders with large firm experience.

Hypothesis 3: Startups created by founders with large firm experience will perform better, in the later years of a startup's life, than those created by founders with small firm experience.

The impact that the characteristics of startups' employees will have on performance has been seldom examined in prior literature (Koch et al. 2013; Rocha et al., 2018). Particularly, to the best of our knowledge, the effect of past managerial experience and size of previous firms of a startup's employees has not been addressed in past research. However, we believe that the impact that such characteristics of a startup's employees have on performance should complement those of its founders. By analysing the characteristics of the employees, and not just those of the founders, we can understand how they impact the outcomes of startups, via increasing its productivity and performance, and if different employee characteristics may improve startup performances at different stages of the firm's lifecycle. In fact, startups who hire more employees with prior managerial experience, which are likely more skilled workers than those without such experience, would allow the startup to draw from their knowledge and skills, which could increase its productivity (Bender et al., 2018). Similarly, if prior experience in small firms benefits startup founders in the early years, while experience in large firms proves more valuable in later stages, then startups with employees who have more small firm experience should perform better initially, whereas those with employees from large firms should excel in later years.

Taking all this into account, we formulate our last three hypotheses:

Hypothesis 4: The percentage of employees with prior managerial experience is positively correlated with startup performance.

Hypothesis 5: The percentage of employees with prior small firm experience has an effect on performance that is decreasing with startup age.

Hypothesis 6: The percentage of employees with large firm experience has an effect on performance that is increasing with startup age.

4.4. Data and Methodology

4.4.1. Data and Sample Construction

In this study we use two datasets: *Quadros de Pessoal* (QP) and *Sistema de Contas Integradas de Empresas* (SCIE). QP is a Portuguese longitudinal matched employer-employee dataset with detailed information on private firms that have at least one wage earner. The dataset has information at the individual level (e.g., age, gender, hierarchical job level, and formal education level), and at the firm level (e.g., number of employees, industry and geographical location). No information is available regarding the primary sector, nor the public sector. The dataset originates from administrative data collected by the Portuguese Ministry of Employment and Social Security through a mandatory yearly survey. QP has been used extensively in past studies (e.g., Baptista et al., 2008; Baptista et al., 2013; Mata & Alves, 2018; Rocha et al., 2018; and Carias et al., 2023).

SCIE, a dataset originating also from administrative data collected by the Portuguese Government, provides further information at the firm-level, namely economic-finance related variables, as the annual sales and gross value added that each firm registered.

We focus on firms created between 2010 and 2019. Each firm is followed either until 2019 (the last year of data available to us), or until the firm is no longer in QP. We consider only firms for which we have information on who the founder is, as this is crucial information for our study. We also consider only firms for which we have information on the gross value added they had in the years observed in the data, as it is one of the variables we use to measure performance. This leaves us with an initial total of 47543 firms.

We exclude firms that start with size one, as these are self-employed individuals, who may have transitioned into entrepreneurship for reasons not related to an accumulation of skills or a discovery of an opportunity, but rather out of necessity stemming from lack of employment opportunities (Baptista et al., 2014). This leaves us with a total of 32362 firms.

We further restrict our sample, by excluding firms that survived for less than two years. By doing so, we exclude firms with short survival times, who exited the dataset shortly after being created, and which could skew our results. This leaves us at the final number of 24677 firms.

4.4.2. Variables and Descriptive Statistics

In this study, we consider founders as workers who are identified as business owners of a startup in its year of creation. QP allows us to pinpoint which workers are business owners and those who are not.

We use two different dependent variables to measure startup performance: Labor Productivity (LP), given by the Gross Value Added divided by the number of employees in the startup, and Firm Size (FS), given by the number of employees in the firm.

We are interested in understanding if the past firm size and managerial experience of both founders and employees will impact the performance of the startups in our sample. To obtain this information, we take data for each founder and employee starting from the year 2000, or from the first year in which they are observed in the dataset, and record info regarding past firm size and managerial experience.

Regarding managerial experience, QP has a variable stating the job level each worker has within a firm. Managers are categorized as holding the two top levels in a firm's hierarchy. We record how many years of managerial experience the founders and employees of the startups in our sample had, prior to creating or joining the startup.

To gather information on past firm size, we observe the last firm in which founders and employees of the startups of analysis worked at, prior to creating or joining the startup, and calculate the mean number of employees the firm had during the period of time in which they worked there.

We also include startup age as a covariate, to assess whether the impact of founders' and employees' past managerial experience and past firm size varies across different stages of startups' lifecycles.

Our regressions also control for other characteristics of the founders and of the employees, that are commonly used in entrepreneurial research. From the founder's side, we include variables stating their age at firm creation, their gender, if they have higher education, if their startup is in the same industry in which they previously worked at, and a variable indicating the number of years they were outside the dataset prior to creating their startup[26]. Regarding the employees, we include the percentage of employees with higher education, the startup's mean employee age and the percentage of employees which are women. At the startup-level, we consider the initial assets, the logarithm of startup's initial size, the industry to which the startup belongs, the region in the country where the startup is located, and if the startup has one or more founders.

In Table 4.1 we present descriptive statistics for our sample. Looking at the table, we can see that most founders come from very small firms, which goes in accordance with the small firm effect. 41.78% of the firms have at least one founder with prior managerial experience, which is also in line with prior literature that suggests that managerial experience is a predictor of entrepreneurial transitions. Only 32.22% of the startups are created by women, which suggests that men are more likely to become entrepreneurs, also in line with prior literature (Minniti & Nardone, 2007; Shahriar, 2018). 21.98% of the startups have founders with higher education. This value, although low, is not surprising, given the low level of education of the Portuguese workforce. Of the founders who do have managerial experience, the average number of years of managerial experience they accumulated is of 5.48, which suggests that managers that end up becoming business owners do so, on average, after

[26] For cases of startups that have more than one founder, the variables regarding the founder characteristics are obtained as follows: if at least one of the founders has prior managerial experience, we consider the startup was created by founders with managerial experience, and similarly for the founder with higher education. For past firm size, we calculate the mean of the past firm sizes of all founders. Regarding founder age at firm creation, we consider the mean age at firm creation of the entrepreneurial team. For the number of years outside the dataset prior to creating their startup, we also consider the mean of this value, for the entrepreneurial team. Lastly, our variable for founder gender is 0 if all entrepreneurs are male, 1 if all entrepreneurs are women, and 2 if it's a mixed entrepreneurial team.

accumulating relevant managerial experience in their past jobs. Founders are, on average, 40.39 years old when starting their businesses, which is line with prior findings (Lévesque & Minniti, 2006; Minola et al., 2016). In our sample, most firms start small, with an average startup size of only 4.48 employees, even after we restrict our sample to firms with startup size 2 or more. The percentage of employees with higher education is of 11.41%. Moreover, startups in our sample hire slightly more men than women, on average. Lastly, the average employee age is similar to that of the founders, being on average, 38.26 years old.

Table 4.1 - Descriptive statistics of the estimation sample.

Number of startups	24677
Number of startups whose founder's past firm had less than 5 employees	9028
Number of startups whose founder's past firm had between 6 and 10 employees	4766
Number of startups whose founder's past firm had between 11 and 20 employees	3325
Number of startups whose founder's past firm had between 21 and 50 employees	2831
Number of startups whose founder's past firm had 51 or more employees	4727
Number of startups whose founder has prior managerial experience	10306
Number of startups whose founder is a woman	7949
Number of startups who have both male and female founders	1890
Number of startups with more than 1 founder	5202
Number of startups whose founder has higher education	5422
Average number of years of founder's past managerial experience	5.48 (4.34)
Average founder age when creating the startup	40.39 (9.03)
Average startup size	4.48 (6.59)
Average percentage of employees with higher education	11.41 (27.31)
Average percentage of women employees	46.51 (41.79)
Average employee age	38.26 (8.83)

Notes: Standard errors in parentheses

4.4.3. Methodology

To analyse how the characteristics of the founders and employees impact the performance of startups, we estimate Correlated Random Effect models (CRE). CRE are a class of econometric techniques that provide an alternative to fixed-effects models when analyzing panel data. In this study, fixed-effect models are not an ideal model choice, as we are interested in analysing characteristics of the founders and employees prior to creating or joining the startups, which are time-fixed variables in our sample.

One of the key advantages of CRE models is that they combine the benefits of both fixed-effects and random-effects models. Like fixed-effects models, they account for endogeneity by incorporating individual-specific effects, but, unlike fixed-effect models, they also allow for the inclusion of time-invariant variables (Mundlak, 1978).

The practical implementation of CRE models introduces a technical distinction from traditional random-effects models: the inclusion of the within-individual averages of time-varying variables as covariates. This approach, as described in Mundlak (1978) and Wooldridge (2010) ensures that the individual-specific effects are explicitly modelled as a function of these averages. By doing so, CRE models capture the correlation between unobserved heterogeneity and the explanatory variables, addressing a key limitation of standard random-effects models.

Startups in our sample may survive for different periods of time, between two years (as we exclude startups that survive for less than that), up until those that never close during our period of analysis. This means that the startups that survive longer have more observations in our sample, and contribute more to the analyses than the startups that are observable for shorter periods of time. This could bias the results, as startups that survive longer likely have better performances than those that close earlier. To address this, our CRE regressions are weighted by the inverse of the predicted probabilities of startup survival. To obtain these weights, we perform maximum likelihood estimation for parametric regression survival-time models, following an exponential survival distribution (Allison, 1982)[27]. We then obtain each observation's predicted survivor probability, and calculate the mean survivor probability for each startup. The inverse of this mean probability is used as a weight in the CRE regressions. As such, startups that have lower survival probabilities will contribute more to the CRE regressions of performance. This should lessen the problem of startups that survive longer being overly represented in our sample of analysis. Similar procedures have been used by, for example, Castro-Silva & Lima (2023), who use the predicted probability of finding a job in a small firm to mitigate for bias stemming from self-selection of more capable workers into larger firms.

4.5. Results

4.5.1. Characteristics of the Founders

We start our analyses by examining if the characteristics of a startup's founders affect performance. The results of these analyses are shown in Table 4.2, which includes four models: Models 1 and 2 use as dependent variable the logarithm of Labor Productivity (LP), calculated

[27] Results for this regression shown in Table 4.A.1, in Appendix 4.A

as the Gross Value Added divided by the number of employees in the startup; Models 3 and 4 use the logarithm of firm size (FS) (number of employees in the startup). Regarding the main independent variables, Models 1 and 3 use the logarithm of the past firm of the startups' founders, and a binary variable indicating if the founder has managerial experience. In Models 2 and 4, we divide the founders into four distinct categories, as per the firm size of their firm of origin and their managerial experience: Non-managers of small firms; Non-managers of large firms; Managers of small firms; Managers of large firms. The coefficients for non-managers of small firms are not presented, as they are the base category to which the other three categories are compared. We consider founders that come from firms of origin with size 20 or less as coming from small firms, and those that come from firms of origin with size of more than 20 as coming from large firms. We divide small and large firms in such a way, as the majority of entrepreneurs come from firms with less than 20 employees (and over one third even from very small firms with less than 5 employees), as we can see in Table 4.1

Starting with Model 1, we can see that the logarithm of the founders past firm size is negatively correlated with the logarithm of LP, which goes in accordance with the small firm effect. We also see that the coefficient for the variable indicating that founders have prior managerial experience is positive, also as expected based on past literature. Model 2 shows results that complement these findings by combining whether founders have managerial experience with whether they come from small or large firms. We can see that startups created by managers from small firms perform better than the base category (non-managers from small firms), and that there is no significant difference in performance between both categories of founders from large firms, and the base category.

Models 3 and 4, which use the logarithm of firm size as the dependent variable, suggest different conclusions. Model 3 shows positive coefficients for both founder's past firm size and founder's managerial experience. Model 4 shows that, while startups created by managers from small firms do not show significantly different performance compared to the base category, those created by founders coming from large firms show positive coefficients. Moreover, additional tests reveal that the coefficient for managers of large firms is significantly larger than that of non-managers of large firms (significant at 95%).

Table 4.2 – Correlated random effects marginal effects for impact of founder's characteristics on performance.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(FS)	Model 4: Log(FS)
Log(Founder's past firm size)	-0.010**		0.013***	
	(0.005)		(0.001)	
Founder has prior managerial experience	0.057***		0.011**	
	(0.019)		(0.005)	
Founder with no managerial experience, coming from large firm		-0.015		0.044***
		(0.024)		(0.007)
Founder with managerial experience, coming from small firm		0.060***		-0.002
		(0.022)		(0.006)
Founder with managerial experience, coming from large firm		0.052		0.088***
		(0.032)		(0.009)
Founder has higher education	0.074***	0.069***	0.045***	0.041***
	(0.025)	(0.025)	(0.007)	(0.007)
Founder's age at firm creation	0.002**	0.003**	-0.002***	-0.002***
	(0.001)	(0.001)	(0.0002)	(0.0002)
Years of non-employment prior to firm creation	-0.006*	-0.006*	-0.006***	-0.006***
	(0.003)	(0.003)	(0.001)	(0.001)
Founder is female	-0.047**	-0.047**	-0.023***	-0.021***
	(0.020)	(0.020)	(0.006)	(0.006)
Firm has both male and female founders	0.011	0.012	-0.020*	-0.019*
	(0.038)	(0.038)	(0.011)	(0.011)
More than 1 founder	0.056**	0.056**	0.070***	0.069***
	(0.027)	(0.027)	(0.007)	(0.007)
Firm age	-0.089***	-0.090***	-0.015**	-0.015**
	(0.023)	(0.023)	(0.006)	(0.006)
Log (Startup size)	0.158***	0.157***	0.843***	0.842***
	(0.017)	(0.017)	(0.004)	(0.004)
Percentage of employees with higher education	-0.001**	-0.001**	-0.001***	-0.001***
	(0.001)	(0.001)	(0.0001)	(0.0002)
Average employee age	0.001	0.001	-0.005***	-0.005***
	(0.001)	(0.001)	(0.0004)	(0.0003)
Percentage of women	0.034	0.034	-0.031***	-0.031***
	(0.036)	(0.036)	(0.007)	(0.007)
Observations	87695	87695	87695	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 and 3 control for firm size dummies. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

Overall, these findings suggest that startups created by founders stemming from small firms, and with managerial experience, are the ones with better financial performance values. However, when it comes to firm size, startups created by founders coming from large firms are larger than those created by founders coming from small firms.

To test Hypotheses 2 and 3, we analyse if the characteristics of a startup's founders have a different impact on performance for different startup ages. To do so, we construct regressions that include the interaction of the characteristics of the startup's founders with the startup's age.

In Figure 4.1 we show the results of a model that includes the interaction of the logarithm of founder's past firm size with firm age, and use as dependent variable Log (LP). Figure 4.2 displays the results of a model with these same independent variables, but using as dependent variable the Log(FS).

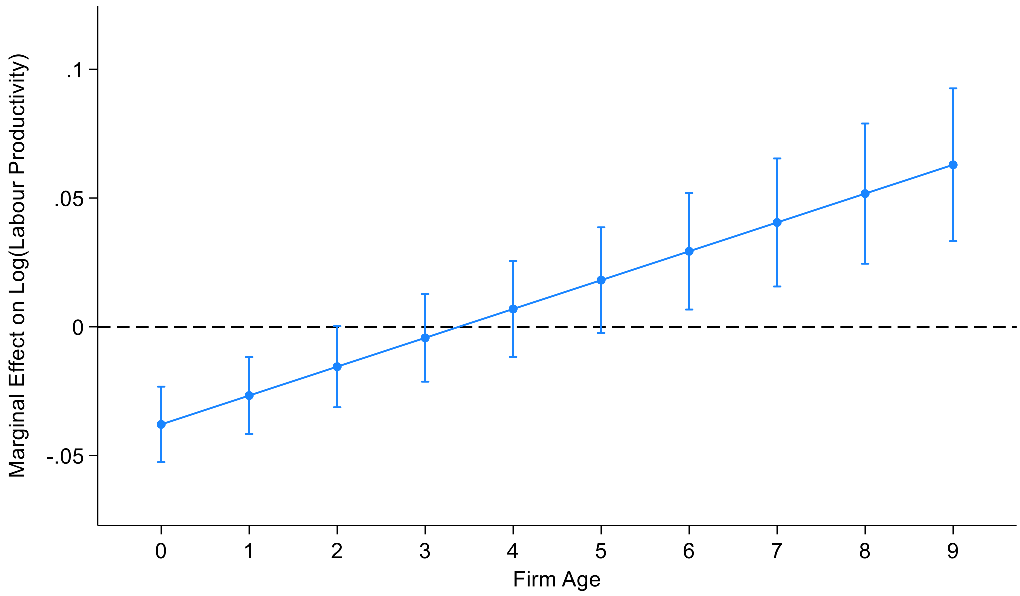

Figure 4.1 - Marginal effects of founder's prior firm size on Log (labour productivity), across firm age.

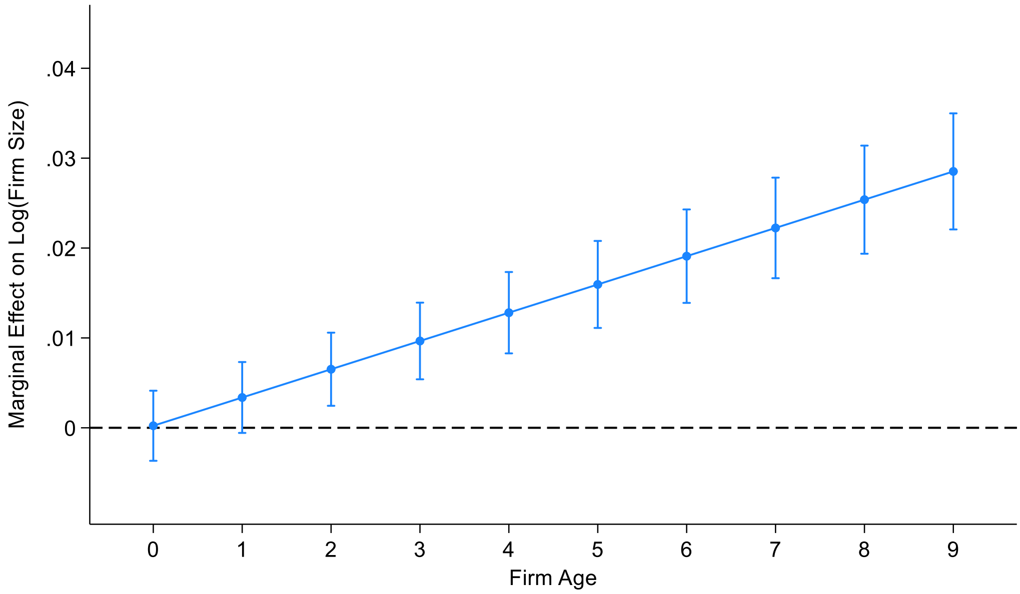

Figure 4.2 - Marginal effects of founder's prior firm size on Log (firm size), across firm age.

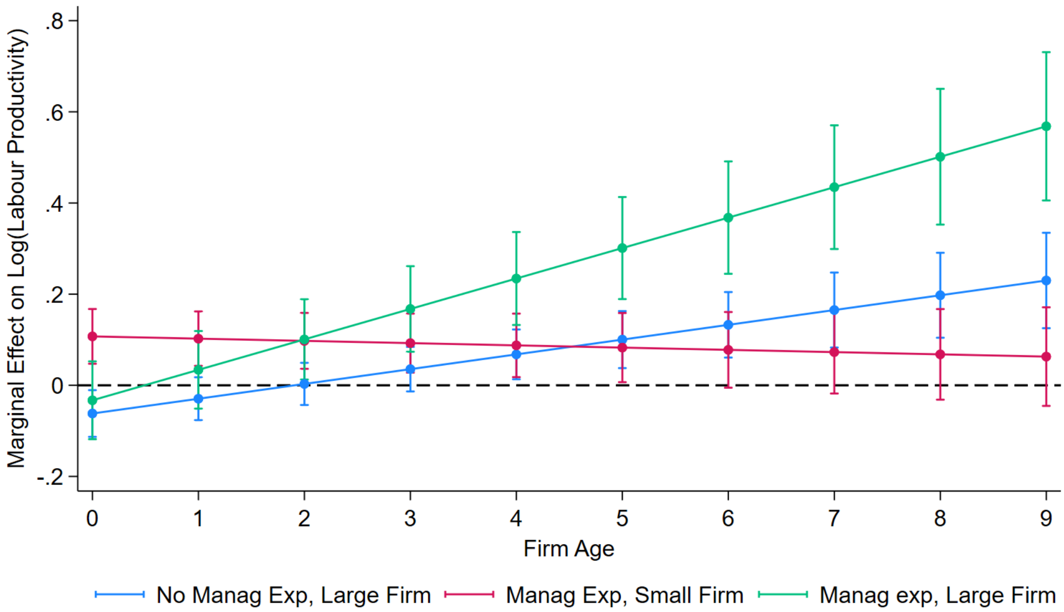

Figure 4.3 - Marginal effects of startup's founder's category on Log (labour productivity), across firm age.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

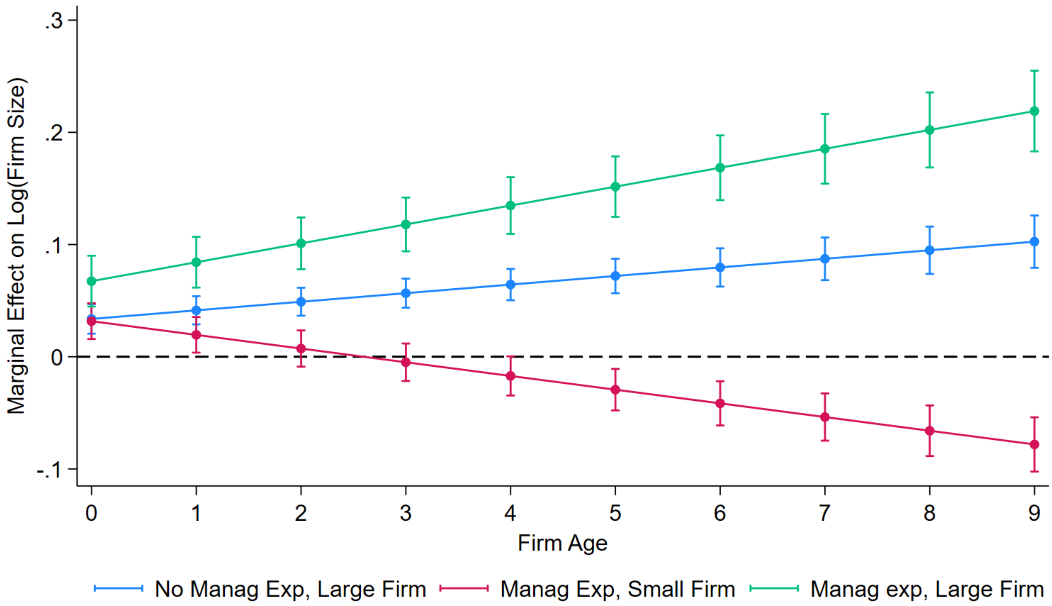

Figure 4.4 - Marginal effects of startup's founder's category on Log (firm size), across firm age.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

In Figure 4.3 we present the results of a model that includes the interaction of startup age and the four categories of types of founders (as shown in the regressions displayed in

Models 2 and 4 of Table 4.2), on Log(LP). Figure 4.4 repeats this regression, but using Log(FS) as the dependent variable. For both models, the base category represents founders without managerial experience, from small firms.

Figures 4.1 and 4.2 show that founder's past firm size has an increasing marginal effect on both Log(LP) and Log(FS), as startups age. In fact, the marginal effect starts negative in Figure 4.1, and non-significant in Figure 4.2, but starting from age six and older (Figure 4.1) and two and older (Figure 4.2) it becomes significantly different from zero, and keeps increasing from then on.[28]

Figure 4.3 shows that, before the second year of a startup's life, all startup types exhibit roughly similar performances. However, this changes as startups age. Starting from the age of five years, startups whose founders were managers from large firms start outperforming startups created by any of the other 3 founder categories. Moreover, while the effect on performance increases with firm age for startups whose founder has no managerial experience and comes from a large firm, for startups whose founder was a manager in small firms, this effect is decreasing with firm age.

Figure 4.4 indicates that, starting from age 1, the startups whose founders were managers in large firms become the largest out of all categories. Moreover, starting from age two, startups whose founders were non-managers of large firms outsize those whose founders were managers in small firms. In fact, the results show that startups whose founders were managers of small firms tend to decrease in size as they age, becoming even smaller than the ones created by non-managers of small firms.

Taken together, these results suggest that, initially, the startups created by founders coming from small firms perform similarly, or even outperform those created by founders coming from larger firms, but that this changes for later years of startups' lives. Particularly, startups founded by managers of large firms, after the initial years, both outsize and outperform those created by the three other founder types.

[28] We also ran regressions which include the interaction of the founders managerial experience and firm age, on Log(LP) and Log(FS). The results, shown in Figures 4.A.1 and 4.A.2, in Appendix 4.A, show overlapping confidence intervals for all startup ages, which indicates that the effect of the founders managerial experience on performance does not differ with startup age.

4.5.2. Characteristics of the Workforce

To further understand what characteristics of a startup may impact its performance, we run models in which we examine if the traits of a startup's employees also affect its performance. Namely, we examine if a higher percentage of employees with prior managerial experience is associated with better firm performance (Hypothesis 4). Moreover, we investigate if there are differences in performance between startups who hire more employees coming from small firms when compared with those who hire more employees coming from large firms, and between those who hire more employees with managerial experience coming from small firms when compared with those who hire more employees with managerial experience coming from large firms.

We show our first results in Table 4.3, which has three different models: in Model 1, the regression includes the percentage of employees without managerial experience and the percentage of employees with managerial experience; in Model 2, the regression includes the percentage of employees coming from small firms and the percentage of employees coming from large firms; in Model 3, the regression includes the percentage of employees coming from small firms and without managerial experience, the percentage of employees coming from large firms and without managerial experience, the percentage of employees coming from small firms and with managerial experience and the percentage of employees coming from large firms and with managerial experience. All three models use as dependent variable the Log(LP).

Model 1 indicates that the percentage of employees with managerial experience has a positive and significant coefficient, while the percentage of employees without managerial experience has no significant impact on performance. These findings provide support for our Hypothesis 4. Model 2 suggests that a higher percentage of employees coming from small firms is positively correlated with performance, and that a higher percentage of employees coming from large firms is negatively related with Log (LP). Similarly, looking at Model 3, we can see that while the two variables regarding employees coming from small firms are associated with better performance, the percentage of employees coming from large firms and without managerial experience is negatively related with the dependent variable, and that the percentage of employees coming from large firms and with managerial experience is not significantly correlated Log (LP). These results suggest, as they did when analysing the characteristics of the founders, that, overall, workers with experience in smaller firms contribute more towards better performing firms than their counterparts with large firm experience.

Table 4.3 – Correlated random effects marginal effects for impact of employees' characteristics on performance.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(LP)
Percentage employees without prior managerial experience	0.0002		
	(0.0003)		
Percentage employees with prior managerial experience	0.002***		
	(0.001)		
Percentage employees coming from small firms		0.001***	
		(0.0002)	
Percentage employees coming from large firms		-0.001**	
		(0.0003)	
Percentage employees without prior managerial experience, coming from small firms			0.001**
			(0.0003)
Percentage employees without prior managerial experience, coming from large firms			-0.001**
			(0.0003)
Percentage employees with prior managerial experience, coming from small firms			0.003***
			(0.001)
Percentage employees with prior managerial experience, coming from large firms			-0.001
			(0.001)
Log(founder's past firm size)	-0.010**	-0.012**	-0.012**
	(0.005)	(0.005)	(0.005)
Founder has prior managerial experience	0.059***	0.058***	0.059***
	(0.020)	(0.019)	(0.020)
Founder has higher education	0.074***	0.073***	0.073***
	(0.025)	(0.025)	(0.025)
Founder's age at firm creation	0.002**	0.003**	0.002**
	(0.001)	(0.001)	(0.001)
Years of non-employment prior to firm creation	-0.006*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)
Founder is female	-0.047**	-0.047**	-0.046**
	(0.020)	(0.020)	(0.020)
Firm has both male and female founders	0.011	0.012	0.012
	(0.038)	(0.038)	(0.038)
More than 1 founder	0.055**	0.055**	0.054**
	(0.027)	(0.027)	(0.027)
Firm age	-0.089***	-0.088***	-0.088***
	(0.023)	(0.023)	(0.023)
Log (Startup size)	0.157***	0.157***	0.156***
	(0.017)	(0.017)	(0.017)
Percentage of employees with higher education	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)
Average employee age	0.0002	0.0004	-0.0002
	(0.001)	(0.001)	(0.001)
Percentage of women	0.039	0.035	0.039
	(0.036)	(0.036)	(0.036)
Observations	87695	87695	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies, and means of all time-varying variables. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

As we did when analysing the characteristics of the founders, we also run regressions that include interactions with the firm's age, to understand if the characteristics of the workforce have different impacts on performance as startups age. This allows us to test our Hypothesis 5 and 6.

Figure 4.5 shows the marginal effects on LP of the percentage of employees coming from small firms, by Firm Age. Figure 4.6 shows the marginal effects on LP of the percentage of employees coming from large firms, by Firm Age.

By analysing Figure 4.5, we can see that the marginal effect, initially, shows significantly positive values, but that decrease with time, becoming non-significantly different from zero starting from age five. This suggests that a higher share of workers from small firms with managerial experience is not correlated with better performance after the initial years.

On the other hand, looking at Figure 4.6, we can see that the marginal effects of having a higher percentage of employees from large firms with managerial experience, although negative at first, become positive and statistically different from zero starting at firm age seven, and consistently increase as firms age.

Taken together, these findings provide support for our Hypotheses 5 and 6.

Lastly, we run regressions that include the interaction of firm age with the four variables included in Model 3 of Table 4.3 which classify employees when it comes to their prior firm size and managerial experience. The results are shown in Figure 4.7.

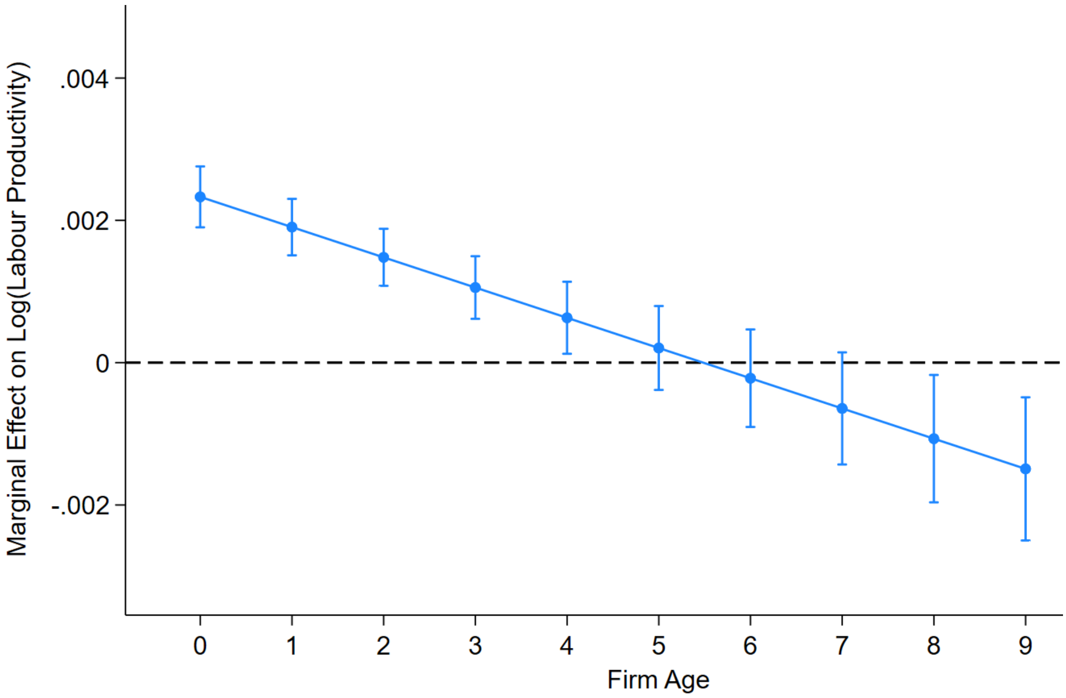

Figure 4.5 -

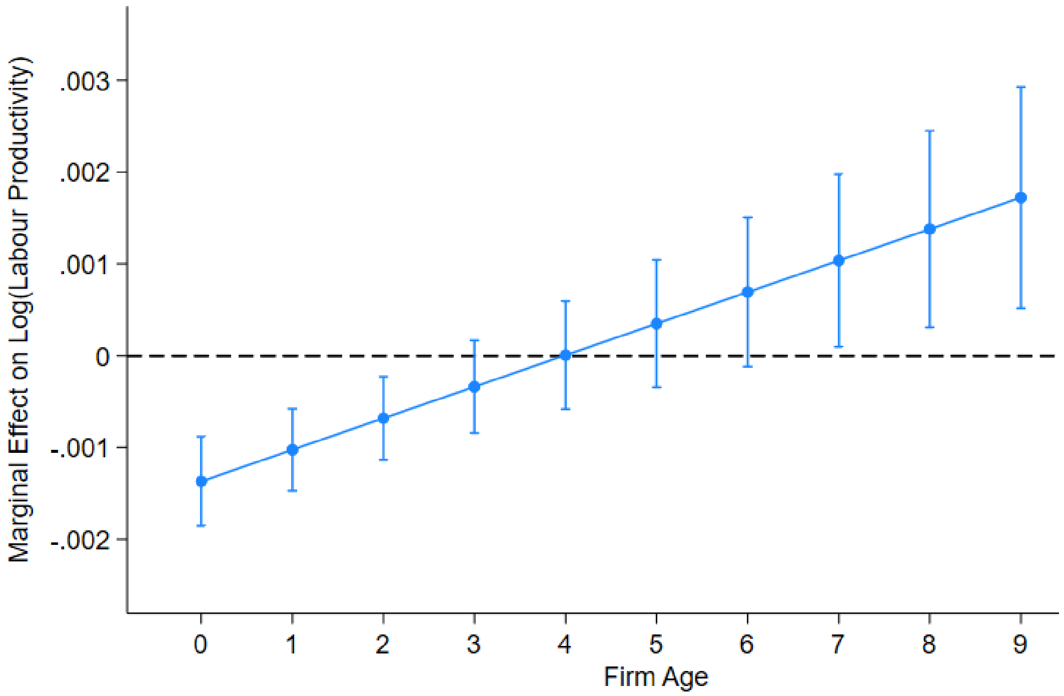

Figure 4.6 - Marginal effect of the percentage of employees coming from large firms (more than 20 employees) on Log (labour productivity), across firm age.

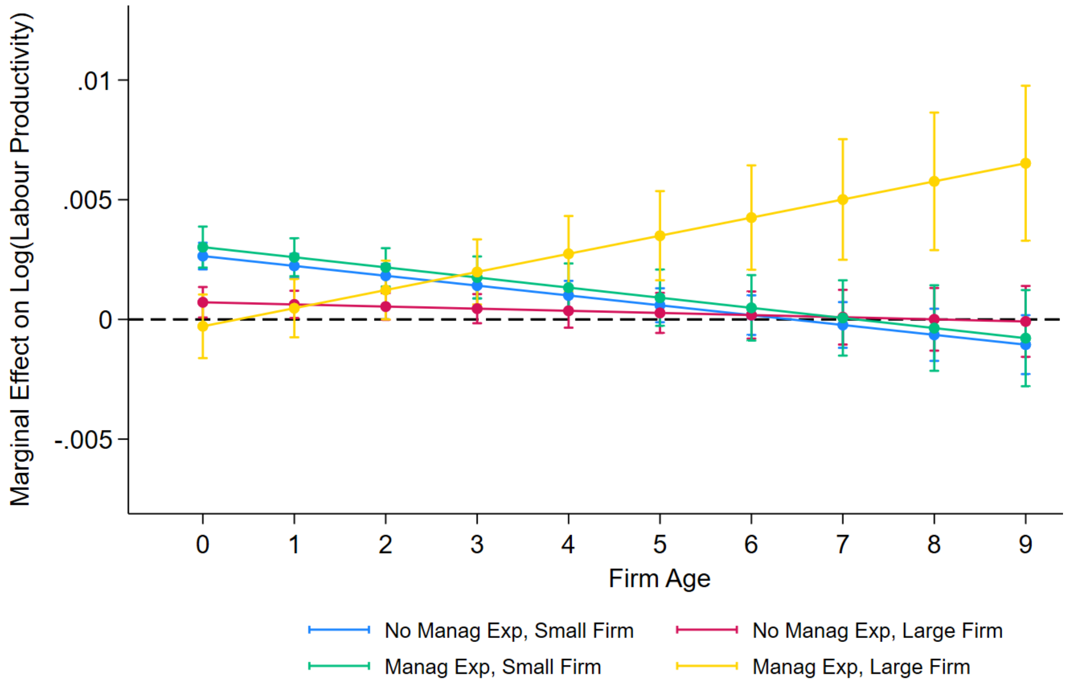

Figure 4.7 - Marginal effects of employees categories on Log (labour productivity), across firm age.

Looking at Figure 4.7, we can see that the only category of employees that has an effect on Log(LP) that is increasing with age is that of those who had managerial experience and come from large firms. In fact, while a higher share of employees coming from small firms (with and without managerial experience) is initially associated with positive performance, the marginal effects for both these categories decrease as firms mature, eventually becoming non-statistically different from zero. These results further support that workers who had managerial experience obtained in larger firms, after the initial years of startups lives, are the ones that most contribute to positive performances.

4.5.3. Robustness Analyses

4.5.3.1. Regressions without Weights

For robustness sake, we run the main regressions in our sample without including the weights for the inverse probability of survival. The results are shown in Tables 4.A.2 and 4.A.3, and Figures 4.A.3 to 4.A.9, in Appendix 4.A. All the main results we can draw from our main analyses are still observable in this robustness check.

4.5.3.2. Regressions with Employee and Founder Fixed Effects

All the main regressions in this study focus solely on observed characteristics of the founders and employees in our sample. However, even though most past studies on the relationship between workforce characteristics and firm performance also exclusively use workers' observed characteristics as their covariates (Hellerstein et al. 1999, Mendes et al. 2010), it is possible that unobserved heterogeneity of both founders and employees also impacts startup productivity. As a robustness check, we construct models that include worker fixed effects obtained from an AKM model, aiming to capture some of the unobservable characteristics of the workforce that may be impacting startup performance, as proposed by Abowd et al. (1999). This AKM model decomposes wages into worker and firm fixed-effects. These worker-fixed effects measure wages as a function of workers' abilities, independent of the characteristics of the firm they work at, and of other personal characteristics included as controls in the AKM model. We then include these fixed-effects in our CRE regressions, as a proxy for unobserved skill. To identify the fixed effects, we restrict the data to include only the largest connected set of workers, which leads to a smaller sample size for these regressions. Bender et al. (2018) is an example of a past study that follows such an approach: the authors use the average of the worker fixed-effects as a proxy for a firm's average human capital, finding that firms with more skilled workforces have higher productivity.

The results including these fixed effects in the regressions can be seen in Tables 4.A.4 and 4.A.5 and Figures 4.A.10 and 4.A.16 in Appendix 4.A. Once more, results are robust.

4.5.3.3. Different Sizes for Small and Large firms

In all the regressions we have shown until now, we consider that individuals stem from small firms if they last worked at a firm with 20 or less employees, and as stemming from large firms if their last firm had more than 20 employees. This choice of cutoff value was due to most founders coming from small firms, as shown in Table 4.1. However, as a robustness check, we run regressions using a more conventional classification, where past experience in small firms is defined as having worked in firms with 50 or fewer employees, and experience in large firms as having worked in firms with more than 50 employees. Results are shown in Tables 4.A.6 and 4.A.7 and Figures 4.A.17 to 4.A.21, in Appendix 4.A. All our main results are robust to this change.

4.5.3.4. Regressions excluding Firms without Original Founders

For some of the firms in our sample, the founders who created them leave the firm, while the firm still remains active. So far in our regressions, we have not excluded such firms for our sample, as we can still measure their performance, even after the original founders have left. However, the firms that keep on operating without any of the original founders present are inherently different from those that retain their original founders. As such, we run regressions in which we exclude all observations of all firms from which the entire entrepreneurial team eventually leaves. Results are shown in Tables 4.A.8 and 4.A.9, and Figures 4.A.22 to 4.A.28, in Appendix 4.A. The results obtained are robust.

4.5.3.5. Years of Managerial Experience

We also run regressions that do not include the binary variable indicating if firms founders have managerial experience or not, but rather the total number of years of prior managerial experience of the founders, by including in the models only the firms whose founders had at least one year of prior managerial experience. The results of regressions which include years of founders' prior managerial experience, and its quadratic form, are presented in Table 4.A.10, in Appendix 4.A. As we can see, when including only the linear form, the coefficient is positive and significant, while the coefficient for its quadratic form is never significant, which suggests that the relationship between years of managerial experience and our dependent variables is positive and linear. This suggests that not only is having managerial experience a predictor of startup success, but that accumulating more years of managerial experience prior to becoming entrepreneurs is also positively related with startup performance.

4.5.3.6. Mediating Effect of Employees' Characteristics

Lastly, we analyse if the impact that startup's founders have on its performance may be mediated by the employees they hire. If founders with managerial experience hire more employees with managerial experience than founders without managerial experience, the difference in firm performance could be due to the characteristics of the startup's workforce. If this is the case, the positive impact of founder's managerial experience on startup performance that we showed in Table 4.2, could be due to a mediating effect by the startup's employees.

Similarly, if any of our founder categories hires more employees coming from large firms, particularly with managerial experience, our results suggest that this could lead their startups to have greater longer term financial performance and growth rates.

To test this, we analyse what type of founders, regarding their past managerial experience and past firm size, hire more employees coming from small and from large firms., separating between employees with managerial experience coming from large firms and those coming from small firms. The results are shown in Figures 4.A.29 and 4.A.30, in Appendix 4.A, which present the marginal effects of founder's previous firm size and managerial experience on the percentage of employees with managerial experience coming from small firms (Figure 4.A.29) and coming from large firms (Figure 4.A.30).

Analysing Figure 4.A.29 we see that, for founders coming from small firms, those with managerial experience are more likely to have a higher share of workers with small firm experience, while the opposite happens for founders coming from large firms. Moreover, we find a negative correlation between past founders' firm size and the share of employees coming from small firms, for founders with managerial experience.

Figure 4.A.30 shows us the mirror image of the last set of results: founders coming from small firms with managerial experience are less likely than founders from small firms with no managerial experience to hire employees coming from large firms, but founders with large firm experience and managerial experience have a higher share of employees coming from large firms than founders from large firms with no managerial experience. We now find a positive correlation between past founders' firm size and share of employees coming from small firms, for both founders with and without managerial experience.

These results go in accordance with our prior findings. In Figure 4.3 we show that in the early years of startups career, those whose founders had managerial experience from small firms are the better performing ones, but that, as startups age, those whose founders had managerial experience from large firms outperform all others. In Figure 4.7 we similarly see that a higher share of employees stemming from small firms is positively associated with performance in startups' early years, but that, for later years, a larger share of employees with managerial experience from larger firms is the one that predicts better performance.

Such results highlight the need to perform mediation analyses, as the impact on performance of the founder's characteristics we examine could (at least partially) take place through the employees they hire in their firms. Particularly, it is possible that the effect on performance of founders with managerial experience coming from small firms is mediated by the percentage of employees with prior managerial coming from small firms (which we will call mediation 1), and that the effect on performance of founders with managerial experience coming from large firms is mediated by the percentage of employees with prior managerial coming from large firms (which we will call mediation 2). In the models we run, we once more interact all these variables with firm age, as the interaction terms are the ones we are interested in analysing.

Following Hessels et al. (2017), we test for mediation effects via assessing the reduction of the coefficient of the variables for founder characteristics, when including the mediating variables in the model (this method, called the difference in coefficients, as proposed by MacKinnon et al. (2002), allows us to obtain the indirect effects). If adding the mediator (the variables indicating the percentage of employees) to the model leads to a decrease in the coefficient of the founder variables, we are in the presence of mediation effects. To test for the significance of the indirect effect, we apply Sobel's (1982) often-used method. Results are shown in Table 4.A.11, in Appendix 4.A. Model 1, which does not include the mediators, gives us the total effect (direct + indirect effect). Models 2 (which uses as mediator the percentage of employees with prior managerial experience, coming from small firms) and 3 (which uses as mediator the percentage of employees with prior managerial experience, coming from large firms), give us the direct effects.

The results shown in Model 2 indicate that the indirect effect of mediation 1 is of 0.001, which means that the mediated percentage is of 22.37%. The results shown in Model 3 indicates that the indirect effect of mediation 2 is of 0.007, which means that the mediated percentage is of 10.27%.

These findings tell us that a portion of the effect that founders have on performance is mediated by the employees they hire. However, the direct effect still accounts for most of the values of the total effects, which does suggest that founder characteristics have a sizeable impact on performance that does not work via the workforce of their startups.

4.6. Discussion

In this study we investigate the role of founders' and employees' prior experiences in shaping startup performance. Our analysis is guided by two key theoretical perspectives from the existing literature. First, we build on the small firm effect, which suggests that individuals with experience in small firms are disproportionately more likely to become entrepreneurs. This effect has been attributed to factors such as broader skill acquisition, greater autonomy, and exposure to multiple aspects of business operations, all of which are also crucial for the success of business owners (Parker, 2009; Elfenbain et al., 2010). Second, we draw on research highlighting the importance of managerial experience for entrepreneurial success. Prior studies emphasize that managerial experience enhances decision-making, strategic planning, and the ability to navigate the complexities of running a business, making it a critical factor in startup performance (Dobrev & Barnett, 2005; Liang et al., 2018). Based on both these branches of past literature, we formulate hypotheses regarding the impact that prior managerial experience, and past firm size of startups' founders and employees will have on startup performance. We test our hypotheses constructing correlated random effect models, using a rich matched employer-employee longitudinal dataset for Portugal.

We propose that startups whose founders have managerial experience will outperform startups whose founders do not. Similarly, we also propose that startups with a larger percentage of employees with managerial experience will have better performances than startups with lower percentage of such employees. Our results support both these hypotheses. By running regressions that use the Logarithm of Labour Productivity and regressions that use the Logarithm of Firm Size as their dependent variables, we find positive coefficients for managerial experience of the founder and for the percentage of employees with managerial experience. These results suggest that managerial experience of both founders and employees is relevant for entrepreneurial success. Moreover, by specifically analysing how startup performance is affected by managerial experience of their founders and employees, we complement the findings of prior findings, who mostly have focused on incumbent firms.

We also theorize that the influence of a startup founder's previous firm size on the startup's performance grows stronger as the startup matures. In the beginning of startups' lives, these must experiment with different strategies, find their most suitable product-market fit, and adapt to an evolving competitive landscape (Aldrich & Fiol, 1994). Founders with small firm experience, who are often used to taking on multiple job roles and adapting to fast-paced and rapidly changing environments (Parker, 2009), may contribute to a startup's ability to perform well in less stable conditions, common during the first years of a startup's life. However, as startups mature, the advantages associated with experience in large firms, such as knowledge on process optimization, and familiarity with scaling strategies, become more significant. Our results go in accordance with this proposal.

Moreover, when coupled with prior managerial experience, our findings suggest that, in the early years, startups founded by individuals with managerial experience obtained in small firms tend to perform similarly to those created by their larger counterparts, but that, as startups age, those created by founders with managerial experience coming from large firms begin outperforming startups created by any other type of founder in our sample. This may suggest that managerial experience, besides being a predictor of startup performance, also allows founders to leverage better the experience obtained in larger firms, leading to better performances as startups mature. Our results may also suggest that founders whose startups are in environments similar to the ones they have experience with will have enhanced performances than if they are working in environments where their past experience is not of direct help (Chandler, 1996).

In addition, we also examine whether startups with a higher share of employees who have experience in small firms perform better during their early years, and whether startups with more employees from large firms outperform others in later years. The results mirror those obtained for the characteristics of the founders, providing support for both the hypotheses.

By creating their own startups, founders with prior work experience can make use of knowledge created by their previous firms that was left underexplored, effectively making use of knowledge spillovers, converting them into potentially profitable enterprises (Acs et al., 2013). Founders with managerial experience from large firms could have been exposed, in their prior jobs, to more complex knowledge and business opportunities than managers from small firms, and than non-managerial workers in larger firms. These more complex projects may be harder to implement, making them riskier, which would explain why startups led by founders with managerial experience from large firms seem to struggle initially. However, upon stabilizing, these ideas generated from knowledge spillovers stemming from larger, stable and successful firms, would likely lead to startups with exceptional performances, as we find for the later years of startups lives.

Interestingly, when examining the impact of founders' past firm size on current startup size, our findings illustrate that startups created by founders with managerial experience from small firms decrease in size, over time. On the other hand, as expected, we find that, after the initial years of activity, startups led by founders with managerial experience from large firms are the largest of all startups in our sample, followed by startups created by founders from large firms, with no managerial experience. For founders with large firm experience, their prior exposure to structured decision-making, resource allocation, and hierarchical structures, more prevalent in large than in small firms (Greiner, 1972), may equip them with the skills needed to manage increasing complexity as their startup grows. In contrast, founders with experience in small firms may be more accustomed to operating in resource-constrained environments with an emphasis on agility and survival, providing them with adaptability that proves advantageous in the uncertain early years of a startup (Bhide, 2000), but that seems to not translate into a long-term growth orientation, limiting the firm's scalability over time. Such results also suggest the startups led by founders with large firm experience may be inherently more growth-oriented than those created by founders with small firm experience.

We also find that, even analysing the subsample of startups whose founders had prior managerial experience, those whose founders had more years of prior managerial experience were better performing. This indicates that not only is managerial experience a predictor of entrepreneurial performance, but that those who accumulate more experience as managers prior to transitioning to entrepreneurship are likely to lead more successful firms. This finding could be key for policy makers who aim to enhance entrepreneurial success. If accumulating managerial experience is positively associated with future startups' outcomes, then it would be beneficial to promote employees to managerial ranks earlier in their lives. Otherwise, if managerial positions are only attainable once workers are older, the managers who would by then have accumulated a vast managerial experience would already be past the age in which entrepreneurial transitions are likely to happen, possibly lowering the number of future high-performing startups.

The results we obtain when examining how employee characteristics impact firm performance mirror those of the founders we have discussed until this point. We show that the impact on performance of the share of employees coming from small firms decreases as startups age, while the opposite is true for the share of employees coming from large firms. Moreover, we highlight that a higher share of employees coming from large firms with managerial experience has a strong impact on startup performance, after the initial years of the firms' lives. These findings indicate that the characteristics of startups' employees are also crucial to analyse startup success, and that future research should not focus solely on the traits of the founders.

We incentivize important extensions to the work done in this study. In our analyses, we do not distinguish between different types of firms closures, but it is possible that the characteristics of founders and employees we examine, besides impacting performance, also influence the likelihood of successful startup closure. Additionally, we focus on objective performance measures, but it could be interesting to examine if the characteristics we analyse also impact subjective performance measures.

4.7. Conclusion

This study examined how past managerial experience and the size of the previous firms of founders and employees impact entrepreneurial success. While previous studies have often focused on how these traits affect the likelihood of individuals becoming entrepreneurs, we investigate how these characteristics influence firm-level performance after the transition occurs. Moreover, past research that analyses startup performance has largely focused on the qualities of the founders alone, ignoring how startups' employees may impact entrepreneurial outcomes. As such, with our analyses, we have aimed to fill these gaps in the literature.

Past research suggests that firms whose founders have managerial experience tend to outperform those whose founders do not (Lazear, 2005; Kim et al., 2006). Our results indicate that startups created by founders with managerial experience consistently outperform those without such leadership, showing support to these findings of prior literature. Similarly, we show that a higher share of employees with managerial experience positively contributes to startup performance.

Past studies also theorize a small firm effect, according to which small firm experience is a strong predictor of entrepreneurial transitions, as workers in small firms develop broad skillsets by working in varied tasks within their jobs (Parker, 2009). These diverse skills could be helpful for the success of startups, particularly in their early stages. Our analyses show that the impact of founders' and employees' past firm size on performance varies as startups age. In the early years, startups created by founders with small firm experience perform better, likely benefiting from the broad skillsets and adaptability these founders bring. However, as startups age, the advantages associated with large firm experience become prevalent. Moreover, we show that the best-performing startups, after the initial years, are those whose founders have both large firm and managerial experience. The findings regarding employee characteristics mirror those of the founders. A higher share of the workforce with small firm experience is more beneficial during the early years of startups lives, whereas large firm experience, particularly when coupled with managerial experience, enhances performance in later stages.

By analysing both founder and employee characteristics in a single analytical framework, and by testing how their impacts on startup performance evolve over a startup's lifecycle, our study provides in-depth understanding of the drivers of entrepreneurial success.

4.A. Appendix

Table 4.A.1 – Piecewise exponential survival model.

Startup age 1 to 3	-0.147***
	(0.024)
Startup age 4 to 6	-0.313***
	(0.033)
Startup age 7 or more	-0.475***
	(0.047)
Founder has higher education	0.0004
	(0.042)
Founder's age at firm creation	-0.009***
	(0.002)
Founder comes from non-employment	0.125***
	(0.022)
Founder is a Woman	0.103***
	(0.029)
More than 1 founder	-0.053**
	(0.026)
Log (Firm size)	-0.914***
	(0.198)
Log (Startup size)	0.651***
	(0.024)
Percentage of employees with higher education	0.001
	(0.001)
Average employee age	0.001
	(0.002)
Percentage of women	0.041
	(0.038)
Observations	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, region, industry, and means of all time-varying variants. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Clustered standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.2 – Correlated random effects marginal effects for impact of founder's characteristics on performance, not including weights for inverse probability of survival.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(FS)	Model 4: Log(FS)
Log(Founder's past firm size)	-0.011**		0.014***	
	(0.006)		(0.001)	
Founder has prior managerial experience	0.055***		0.010*	
	(0.021)		(0.006)	
Founder with no managerial experience, coming from large firm		-0.020		0.048***
		(0.026)		(0.007)
Founder with managerial experience, coming from small firm		0.056**		-0.002
		(0.023)		(0.006)
Founder with managerial experience, coming from large firm		0.047		0.091***
		(0.035)		(0.010)
Founder has higher education	0.084***	0.081***	0.045***	0.042***
	(0.029)	(0.029)	(0.008)	(0.008)
Founder's age at firm creation	0.002**	0.003***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.0003)	(0.0003)
Years of non-employment prior to firm creation	-0.004	-0.006*	-0.007***	-0.007***
	(0.003)	(0.003)	(0.001)	(0.001)
Founder is female	-0.059**	-0.050**	-0.021***	-0.021***
	(0.023)	(0.023)	(0.006)	(0.006)
Firm has both male and female founders	-0.004	0.008	-0.019	-0.019
	(0.038)	(0.037)	(0.012)	(0.012)
More than 1 founder	0.065**	0.064**	0.068***	0.069***
	(0.026)	(0.026)	(0.009)	(0.009)
Firm age	-0.111***	-0.083***	-0.004	-0.006
	(0.033)	(0.031)	(0.006)	(0.007)
Log (Startup size)	0.174***	0.165***	0.843***	0.843***
	(0.018)	(0.018)	(0.005)	(0.005)
Percentage of employees with higher education	-0.001	0.163***	-0.001***	0.843***
	(0.001)	(0.018)	(0.0002)	(0.005)
Average employee age	0.001	-0.001	-0.005***	-0.001***
	(0.002)	(0.001)	(0.0002)	(0.0003)
Percentage of women	0.029	0.001	-0.028**	-0.005***
	(0.050)	(0.002)	(0.013)	(0.0002)
Observations	87695	87695	87695	87695

Notes: Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 and 3 control for firm size dummies. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Clustered standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.3 – Correlated random effects marginal effects for impact of employees' characteristics on performance, not including weights for inverse probability of survival.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(LP)
Percentage employees without prior managerial experience	0.0002		
	(0.0003)		
Percentage employees with prior managerial experience	0.002**		
	(0.001)		
Percentage employees coming from small firms		0.001**	
		(0.0004)	
Percentage employees coming from large firms		-0.001	
		(0.001)	
Percentage employees without prior managerial experience, coming from small firms			0.001*
			(0.0003)
Percentage employees without prior managerial experience, coming from large firms			-0.001
			(0.001)
Percentage employees with prior managerial experience, coming from small firms			0.003***
			(0.001)
Percentage employees with prior managerial experience, coming from large firms			-0.0004
			(0.001)
Log(founder's past firm size)	-0.011*	-0.012**	-0.012**
	(0.006)	(0.006)	(0.006)
Founder has prior managerial experience	0.055***	0.055***	0.056***
	(0.021)	(0.021)	(0.021)
Founder has higher education	0.086***	0.085***	0.085***
	(0.029)	(0.029)	(0.029)
Founder's age at firm creation	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
Years of non-employment prior to firm creation	-0.006*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)
Founder is female	-0.050**	-0.050**	-0.050**
	(0.023)	(0.023)	(0.023)
Firm has both male and female founders	0.007	0.007	0.008
	(0.037)	(0.037)	(0.037)
More than 1 founder	0.064**	0.063**	0.063**
	(0.026)	(0.026)	(0.026)
Firm age	-0.083***	-0.082***	-0.081***
	(0.031)	(0.031)	(0.031)
Log (Startup size)	0.163***	0.163***	0.162***
	(0.018)	(0.018)	(0.018)
Percentage of employees with higher education	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Average employee age	0.0002	0.001	-0.0002
	(0.002)	(0.002)	(0.002)
Percentage of women	0.041	0.038	0.041
	(0.050)	(0.050)	(0.050)
Observations	87695	87695	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies, and means of all time-varying variables. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Clustered standard errors in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

Table 4.A.4 – Correlated random effects marginal effects for impact of founder's characteristics on performance, including worker fixed effects.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(FS)	Model 4: Log(FS)
Log(Founder's past firm size)	-0.027***		0.011***	
	(0.006)		(0.002)	
Founder has prior managerial experience	0.052**		0.016**	
	(0.022)		(0.006)	
Founder with no managerial experience, coming from large firm		-0.045*		0.043***
		(0.026)		(0.007)
Founder with managerial experience, coming from small firm		0.077***		0.006
		(0.026)		(0.007)
Founder with managerial experience, coming from large firm		-0.028		0.080***
		(0.035)		(0.010)
Founder has higher education	0.018	0.015	0.037***	0.035***
	(0.028)	(0.028)	(0.008)	(0.008)
Founder's age at firm creation	0.001	0.001	-0.002***	-0.002***
	(0.001)	(0.001)	(0.0003)	(0.0003)
Years of non-employment prior to firm creation	-0.003	-0.004	-0.007***	-0.007***
	(0.004)	(0.004)	(0.001)	(0.001)
Founder is female	-0.039*	-0.039*	-0.019***	-0.019***
	(0.023)	(0.023)	(0.006)	(0.006)
Firm has both male and female founders	-0.003	-0.002	-0.015	-0.015
	(0.042)	(0.042)	(0.012)	(0.012)
More than 1 founder	0.059**	0.060**	0.068***	0.068***
	(0.029)	(0.029)	(0.008)	(0.008)
Firm age	-0.165***	-0.166***	-0.011	-0.011
	(0.026)	(0.026)	(0.007)	(0.007)
Log (Startup size)	0.175***	0.173***	0.845***	0.844***
	(0.019)	(0.019)	(0.004)	(0.004)
Percentage of employees with higher education	-0.001	-0.001	-0.001***	-0.001***
	(0.001)	(0.001)	(0.0002)	(0.0003)
Average employee age	0.002	0.002	-0.005***	-0.005***
	(0.002)	(0.002)	(0.0004)	(0.0003)
Percentage of women	-0.021	-0.021	-0.049***	-0.049***
	(0.040)	(0.040)	(0.008)	(0.008)
Observations	70838	70838	70838	70838

Notes: All regressions include weights for inverse probability of survival and for founder and employee fixed effects. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 and 3 control for firm size dummies. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.5 – Correlated random effects marginal effects for impact of employees' characteristics on performance including worker fixed effects.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(LP)
Percentage employees without prior managerial experience	0.001***		
	(0.0002)		
Percentage employees with prior managerial experience	0.003***		
	(0.001)		
Percentage employees coming from small firms		0.002***	
		(0.0002)	
Percentage employees coming from large firms		0.0007	
		(0.0006)	
Percentage employees without prior managerial experience, coming from small firms			0.002***
			(0.0004)
Percentage employees without prior managerial experience, coming from large firms			0.0004
			(0.0005)
Percentage employees with prior managerial experience, coming from small firms			0.003***
			(0.001)
Percentage employees with prior managerial experience, coming from large firms			0.001
			(0.001)
Log(founder's past firm size)	-0.027***	-0.028***	-0.028***
	(0.006)	(0.006)	(0.006)
Founder has prior managerial experience	0.054**	0.052**	0.054**
	(0.022)	(0.022)	(0.022)
Founder has higher education	0.018	0.018	0.018
	(0.028)	(0.028)	(0.028)
Founder's age at firm creation	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Years of non-employment prior to firm creation	-0.004	-0.003	-0.004
	(0.004)	(0.004)	(0.004)
Founder is female	-0.038*	-0.039*	-0.038*
	(0.023)	(0.023)	(0.023)
Firm has both male and female founders	-0.002	-0.002	-0.002
	(0.042)	(0.042)	(0.042)
More than 1 founder	0.059**	0.058**	0.058**
	(0.029)	(0.029)	(0.029)
Firm age	-0.165***	-0.164***	-0.163***
	(0.026)	(0.026)	(0.026)
Log (Startup size)	0.173***	0.174***	0.173***
	(0.019)	(0.019)	(0.019)
Percentage of employees with higher education	-0.001	-0.0004	-0.001
	(0.001)	(0.001)	(0.001)
Average employee age	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Percentage of women	-0.015	-0.020	-0.015
	(0.040)	(0.040)	(0.040)
Observations	70838	70838	70838

Notes: All regressions include weights for inverse probability of survival and for founder and employee fixed effects. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies, and means of all time-varying variables. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

Table 4.A.6 – Correlated random effects marginal effects for impact of founder's characteristics on performance, using alternative measures for small and large firms.

	Model 1: Log(LP)	Model 2: Log(FS)
Founder with no managerial experience, coming from large firm	-0.065**	0.011
	(0.028)	(0.008)
Founder with managerial experience, coming from small firm	0.056***	-0.005
	(0.021)	(0.006)
Founder with managerial experience, coming from large firm	0.008	0.072***
	(0.038)	(0.010)
Founder has higher education	0.074***	0.047***
	(0.025)	(0.007)
Founder's age at firm creation	0.002**	-0.002***
	(0.001)	(0.0004)
Years of non-employment prior to firm creation	-0.006*	-0.006***
	(0.003)	(0.001)
Founder is female	-0.047**	-0.023***
	(0.020)	(0.006)
Firm has both male and female founders	0.011	-0.019*
	(0.038)	(0.011)
More than 1 founder	0.055**	0.069***
	(0.027)	(0.007)
Firm age	-0.089***	-0.015**
	(0.023)	(0.006)
Log (Startup size)	0.157***	0.846***
	(0.017)	(0.004)
Percentage of employees with higher education	-0.001**	-0.001***
	(0.001)	(0.0003)
Average employee age	0.001	-0.005***
	(0.001)	(0.0002)
Percentage of women	0.034	-0.031***
	(0.036)	(0.007)
Observations	87695	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 controls for firm size dummies. Past firm size small for firms with 50 or less employees. Past firm size large for firms with more than 50 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.7 – Correlated random effects marginal effects for impact of employees' characteristics on performance, using alternative measures for small and large firms.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(LP)
Percentage employees without prior managerial experience	0.0002		
	(0.0003)		
Percentage employees with prior managerial experience	0.002***		
	(0.001)		
Percentage employees coming from small firms		0.001**	
		(0.0004)	
Percentage employees coming from large firms		-0.001**	
		(0.0005)	
Percentage employees without prior managerial experience, coming from small firms			0.001*
			(0.0004)
Percentage employees without prior managerial experience, coming from large firms			-0.001*
			(0.0006)
Percentage employees with prior managerial experience, coming from small firms			0.002***
			(0.001)
Percentage employees with prior managerial experience, coming from large firms			-0.002
			(0.001)
Log(founder's past firm size)	-0.010**	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)
Founder has prior managerial experience	0.059***	0.057***	0.059***
	(0.020)	(0.019)	(0.020)
Founder has higher education	-0.089***	-0.088***	-0.088***
	(0.023)	(0.023)	(0.023)
Founder's age at firm creation	0.074***	0.075***	0.075***
	(0.025)	(0.025)	(0.025)
Years of non-employment prior to firm creation	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Founder is female	-0.006*	-0.006*	-0.006*
	(0.003)	(0.003)	(0.003)
Firm has both male and female founders	-0.047**	-0.048**	-0.047**
	(0.020)	(0.020)	(0.020)
More than 1 founder	0.011	0.011	0.011
	(0.038)	(0.038)	(0.038)
Firm age	0.055**	0.056**	0.056**
	(0.027)	(0.027)	(0.027)
Log (Startup size)	0.157***	0.157***	0.156***
	(0.017)	(0.017)	(0.017)
Percentage of employees with higher education	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)
Average employee age	0.0004	0.0006	-0.00001
	(0.001)	(0.001)	(0.001)
Percentage of women	0.039	0.035	0.038
	(0.036)	(0.036)	(0.036)
Observations	87695	87695	87695

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies, and means of all time-varying variables. Past firm size small for firms with 50 or less employees. Past firm size large for firms with more than 50 employees. Standard errors in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

Table 4.A.8 – Correlated random effects marginal effects for impact of founder's characteristics on performance, excluding firms without any of its original founders.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(FS)	Model 4: Log(FS)
Log(Founder's past firm size)	-0.012**		0.013***	
	(0.005)		(0.001)	
Founder has prior managerial experience	0.040**		0.008	
	(0.020)		(0.005)	
Founder with no managerial experience, coming from large firm		-0.024		0.045***
		(0.025)		(0.007)
Founder with managerial experience, coming from small firm		0.045**		-0.002
		(0.023)		(0.006)
Founder with managerial experience, coming from large firm		0.016		0.083***
		(0.033)		(0.009)
Founder has higher education	0.085***	0.081***	0.043***	0.039***
	(0.027)	(0.027)	(0.007)	(0.007)
Founder's age at firm creation	0.002**	0.002**	-0.002***	-0.002***
	(0.001)	(0.001)	(0.0003)	(0.0002)
Years of non-employment prior to firm creation	-0.006*	-0.006*	-0.007***	-0.007***
	(0.003)	(0.003)	(0.001)	(0.001)
Founder is female	-0.049**	-0.049**	-0.023***	-0.022***
	(0.021)	(0.021)	(0.006)	(0.006)
Firm has both male and female founders	0.016	0.017	-0.026***	-0.025**
	(0.038)	(0.038)	(0.010)	(0.010)
More than 1 founder	0.050*	0.051*	0.068***	0.068***
	(0.028)	(0.028)	(0.007)	(0.007)
Firm age	-0.079***	-0.079***	-0.007	-0.007
	(0.024)	(0.024)	(0.006)	(0.006)
Log (Startup size)	0.141***	0.139***	0.838***	0.838***
	(0.019)	(0.019)	(0.004)	(0.004)
Percentage of employees with higher education	-0.001	-0.001	-0.001***	-0.001***
	(0.001)	(0.001)	(0.0002)	(0.0002)
Average employee age	0.003**	0.003**	-0.005***	-0.005***
	(0.002)	(0.002)	(0.0003)	(0.0004)
Percentage of women	0.030	0.030	-0.019***	-0.019***
	(0.038)	(0.038)	(0.007)	(0.007)
Observations	79678	79678	79678	79678

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 and 3 control for firm size dummies. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.9 – Correlated random effects marginal effects for impact of employees' characteristics on performance, excluding firms without any of its original founders.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(LP)
Percentage employees without prior managerial experience	0.0002		
	(0.0004)		
Percentage employees with prior managerial experience	0.002***		
	(0.001)		
Percentage employees coming from small firms		0.001***	
		(0.0004)	
Percentage employees coming from large firms		-0.001**	
		(0.0005)	
Percentage employees without prior managerial experience, coming from small firms			0.001**
			(0.0004)
Percentage employees without prior managerial experience, coming from large firms			-0.001**
			(0.0004)
Percentage employees with prior managerial experience, coming from small firms			0.003***
			(0.001)
Percentage employees with prior managerial experience, coming from large firms			-0.001
			(0.001)
Log(founder's past firm size)	-0.011**	-0.012**	-0.012**
	(0.005)	(0.005)	(0.005)
Founder has prior managerial experience	0.031	0.030	0.031
	(0.020)	(0.020)	(0.020)
Founder has higher education	0.083***	0.082***	0.082***
	(0.027)	(0.027)	(0.027)
Founder's age at firm creation	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
Years of non-employment prior to firm creation	-0.008**	-0.008**	-0.008**
	(0.003)	(0.003)	(0.003)
Founder is female	-0.050**	-0.050**	-0.049**
	(0.021)	(0.021)	(0.021)
Firm has both male and female founders	0.005	0.006	0.006
	(0.038)	(0.038)	(0.038)
More than 1 founder	0.057**	0.056**	0.056**
	(0.028)	(0.028)	(0.028)
Firm age	-0.077***	-0.076***	-0.076***
	(0.024)	(0.024)	(0.024)
Log (Startup size)	0.141***	0.141***	0.140***
	(0.019)	(0.019)	(0.019)
Percentage of employees with higher education	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Average employee age	0.002	0.003*	0.002
	(0.002)	(0.002)	(0.002)
Percentage of women	0.020	0.016	0.020
	(0.038)	(0.038)	(0.038)
Observations	79678	79678	79678

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies, and means of all time-varying variables. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.10 – Correlated random effects marginal effects for impact of founder's characteristics on performance, including founder's years of prior managerial experience.

	Model 1: Log(LP)	Model 2: Log(LP)	Model 3: Log(FS)	Model 4: Log(FS)
Log(Founder's past firm size)	-0.017**	-0.017**	0.021***	0.021***
	(0.008)	(0.008)	(0.002)	(0.002)
Founder's years of prior managerial experience	0.012***	0.020**	0.003***	0.005*
	(0.003)	(0.010)	(0.001)	(0.003)
Founder's years of prior managerial experience (squared)		-0.001		-0.0001
		(0.001)		(0.0002)
Founder has higher education	0.065*	0.064*	0.042***	0.042***
	(0.034)	(0.034)	(0.009)	(0.009)
Founder's age at firm creation	0.0003	0.0003	-0.003***	-0.003***
	(0.002)	(0.002)	(0.0005)	(0.0004)
Years of non-employment prior to firm creation	0.001	0.001	-0.005***	-0.005***
	(0.005)	(0.005)	(0.001)	(0.001)
Founder is female	-0.033	-0.032	-0.022**	-0.021**
	(0.032)	(0.032)	(0.009)	(0.009)
Firm has both male and female founders	0.003	0.003	-0.029*	-0.029*
	(0.055)	(0.055)	(0.015)	(0.015)
More than 1 founder	0.048	0.048	0.063***	0.063***
	(0.040)	(0.040)	(0.011)	(0.011)
Firm age	-0.073**	-0.073**	-0.012	-0.013
	(0.036)	(0.036)	(0.010)	(0.010)
Log (Startup size)	0.155***	0.155***	0.856***	0.856***
	(0.026)	(0.026)	(0.006)	(0.006)
Percentage of employees with higher education	-0.001*	-0.001*	-0.001***	-0.001***
	(0.001)	(0.001)	(0.0010)	(0.0002)
Average employee age	0.003	0.003	-0.006***	-0.006***
	(0.002)	(0.002)	(0.0004)	(0.0004)
Percentage of women	-0.022	-0.022	-0.009	-0.009
	(0.053)	(0.053)	(0.010)	(0.010)
Observations	39063	39063	39063	39063

Notes: All regressions include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, and means of all time-varying variables. Models 1 and 3 control for firm size dummies. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 4.A.11 – Correlated random effects marginal effects for impact on performance, analysing for mediation effects

	Model 1: No mediator	Model 2: + Mediator 1	Model 3: + Mediator 2
Founder with no managerial experience, coming from large firm	-0.059*	-0.058*	-0.056*
	(0.031)	(0.031)	(0.031)
Founder with managerial experience, coming from small firm	0.111***	0.105***	0.111***
	(0.036)	(0.037)	(0.037)
Founder with managerial experience, coming from large firm	-0.028	-0.028	-0.013
	(0.052)	(0.052)	(0.052)
Founder with no managerial experience, coming from large firm times firm age	0.032***	0.032***	0.031***
	(0.008)	(0.008)	(0.008)
Founder with managerial experience, coming from small firm times firm age	-0.005	-0.004	-0.005
	(0.007)	(0.007)	(0.007)
Founder with managerial experience, coming from large firm times firm age	0.067***	0.067***	0.060***
	(0.010)	(0.010)	(0.010)
Mediator 1: percentage of employees with prior managerial experience, coming from small firms		0.001**	
		(0.0004)	
Mediator 2: percentage of employees with prior managerial experience, coming from large firms			-0.002**
			(0.001)
Founder has higher education	0.078***	0.078***	0.078***
	(0.025)	(0.025)	(0.025)
Founder's age at firm creation	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Years of non-employment prior to firm creation	-0.005*	-0.005*	-0.005*
	(0.003)	(0.003)	(0.003)
Founder is female	-0.047**	-0.048**	-0.047**
	(0.020)	(0.020)	(0.020)
Firm has both male and female founders	0.006	0.006	0.006
	(0.038)	(0.038)	(0.038)
More than 1 founder	0.059**	0.059**	0.059**
	(0.027)	(0.027)	(0.027)
Firm age	0.295***	0.297***	0.294***
	(0.011)	(0.011)	(0.011)
Log (Startup size)	0.162***	0.163***	0.163***
	(0.017)	(0.017)	(0.017)
Percentage of employees with higher education	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)
Average employee age	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Percentage of women	0.033	0.035	0.035
	(0.036)	(0.036)	(0.036)
Observations	87695	87695	87695

Notes: Mediator 1 is the percentage of employees with prior managerial experience, coming from small firms; Mediator 2 is the percentage of employees with prior managerial experience, coming from large firms. The mediator are interacted with firm age. All regressions also include weights for inverse probability of survival. Regressions also control for: initial startup assets, year dummies, binary variable stating if the firm is in the same industry as the founder's previous industry, region, industry, firm size dummies and means of all time-varying variables. Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees. Standard errors in parentheses.

* p < 0.10; ** p < 0.05; *** p < 0.01.

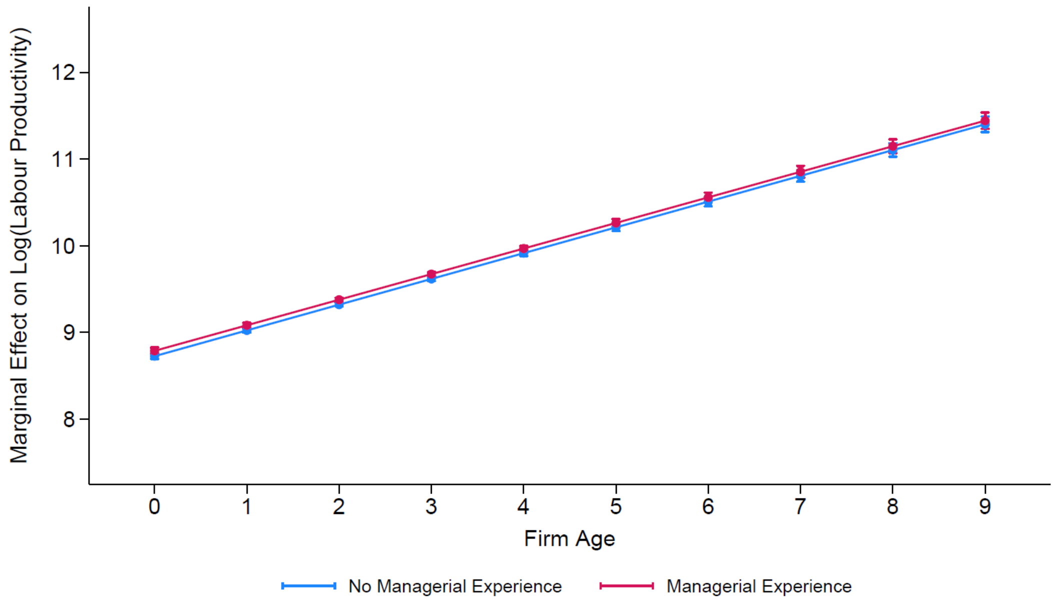

Figure 4.A.1 - Marginal effects of founder's prior managerial experience on Log (labour productivity), across firm age.

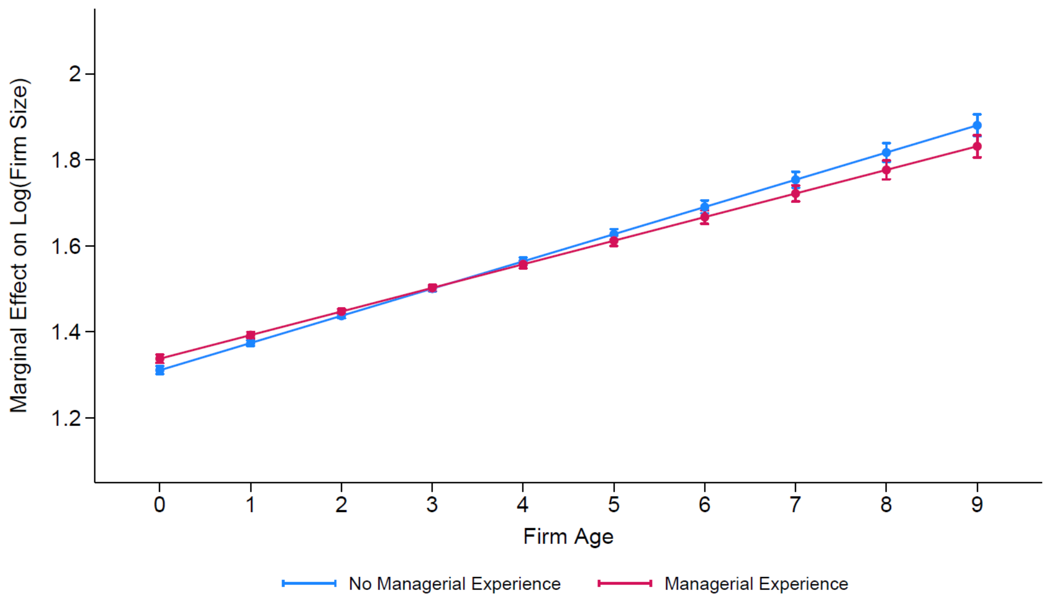

Figure 4.A.2 - Marginal effects of founder's prior managerial experience on Log (firm size), across firm age.

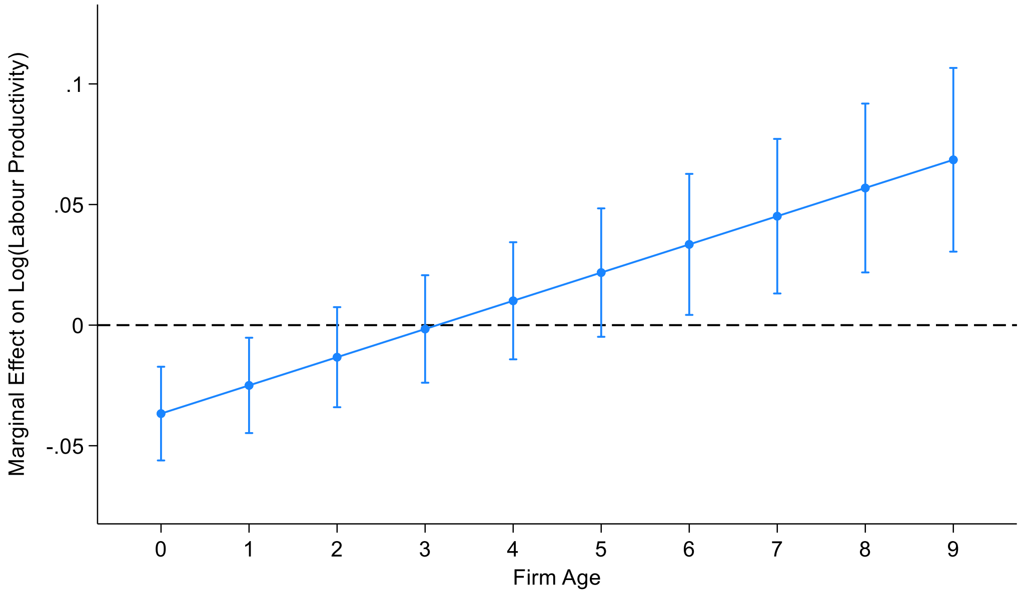

Figure 4.A.3 - Marginal effects of founder's prior firm size on Log (labour productivity), across firm age, not including weights for inverse probability of survival.

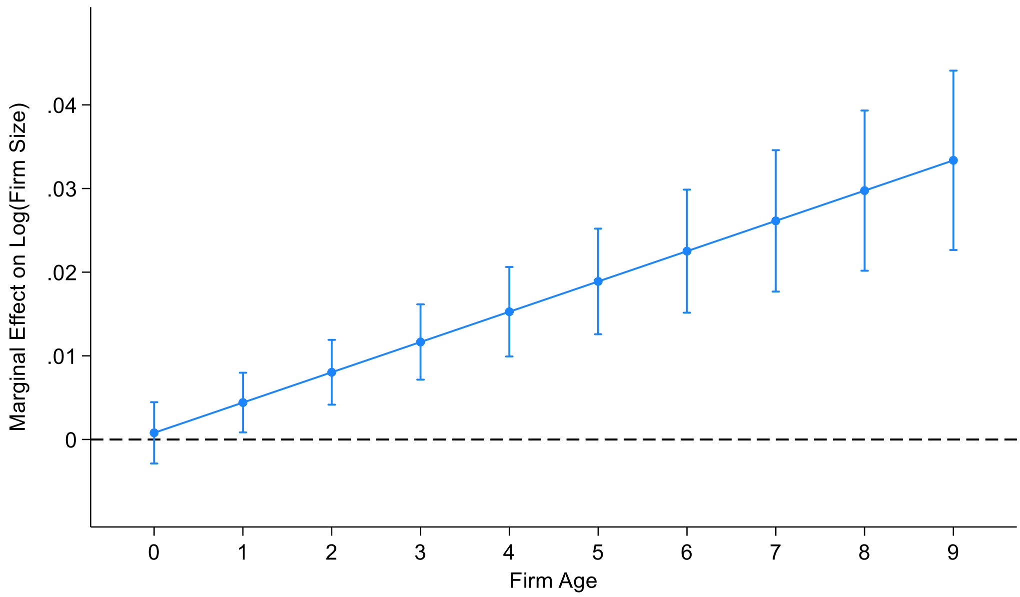

Figure 4.A.4 - Marginal effects of founder's prior firm size on Log (firm size), across firm age, not including weights for inverse probability of survival.

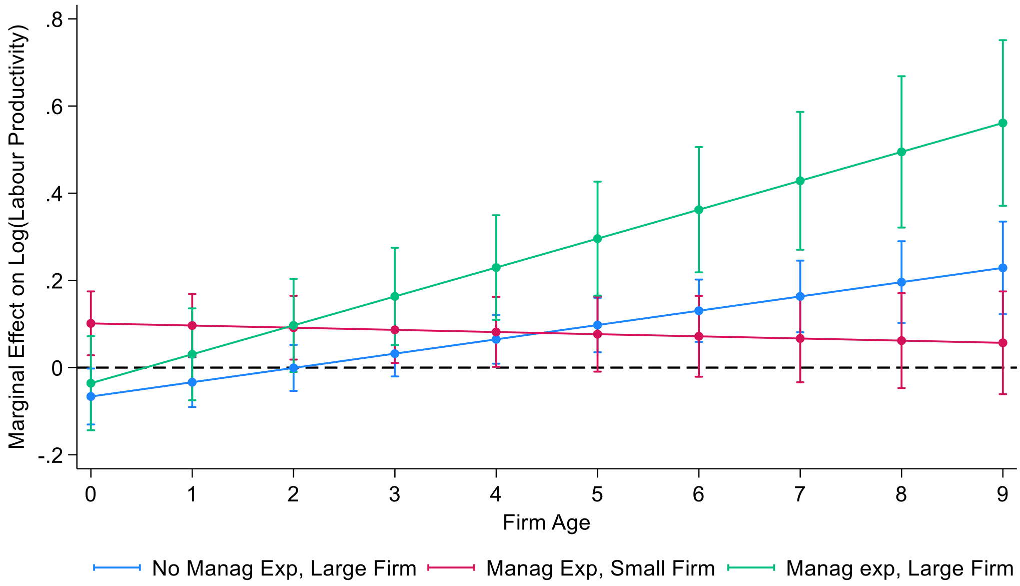

Figure 4.A.5 - Marginal effects of startup's founder's category on Log (labour productivity), across firm age, not including weights for inverse probability of survival.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

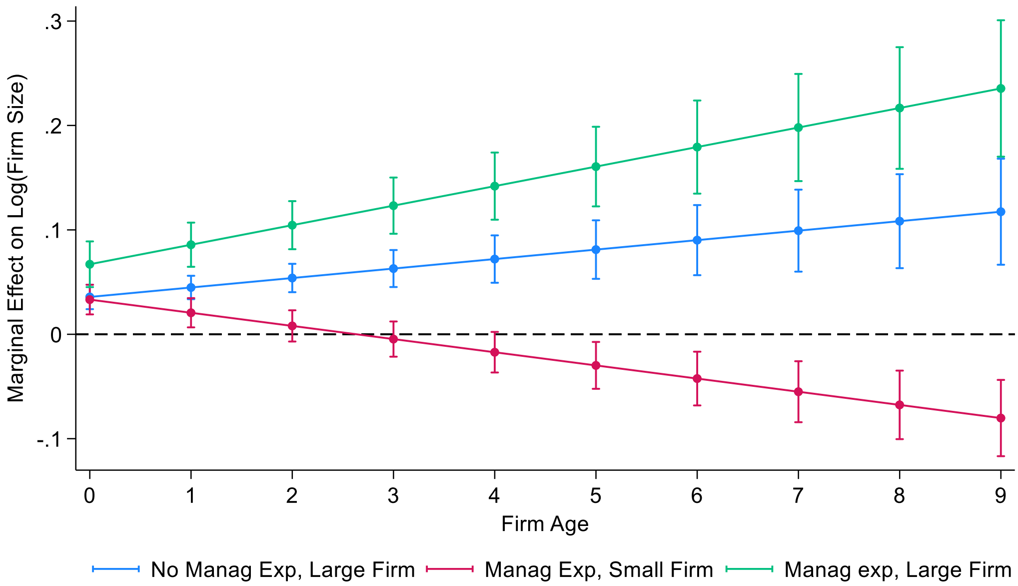

Figure 4.A.6 - Marginal effects of startup's founder's category on Log (firm size), across firm age, not including weights for inverse probability of survival.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

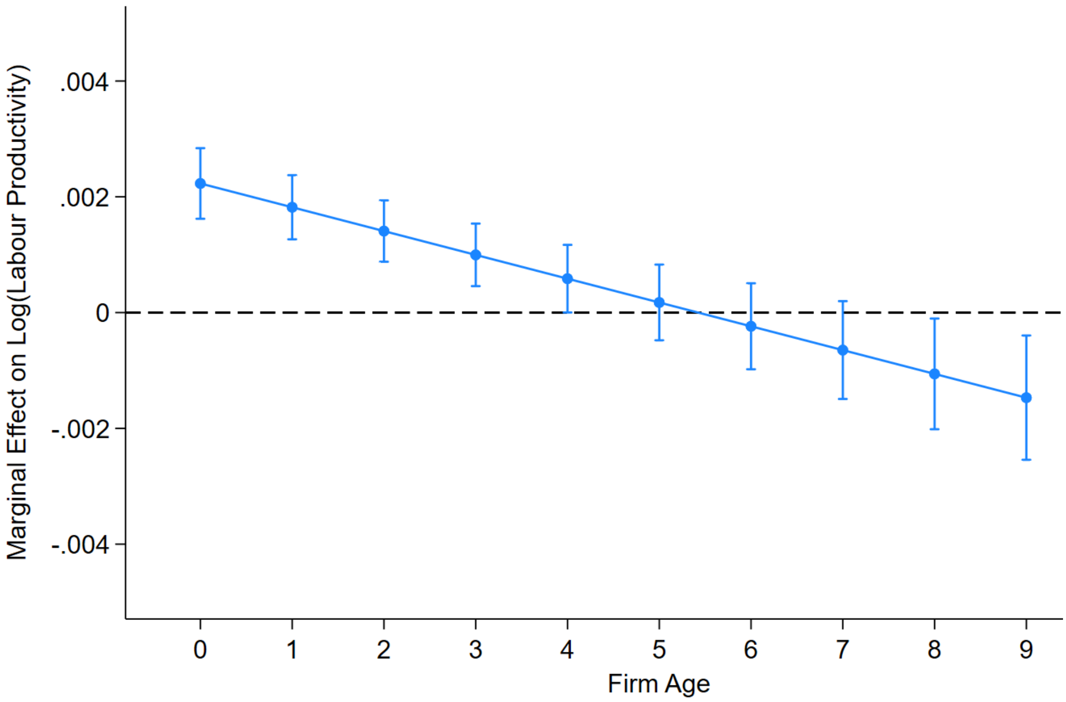

Figure 4.A.7 - Marginal effect of the percentage of employees coming from small firms (with 20 or less employees) on Log (labour productivity), across firm age, not including weights for inverse probability of survival.

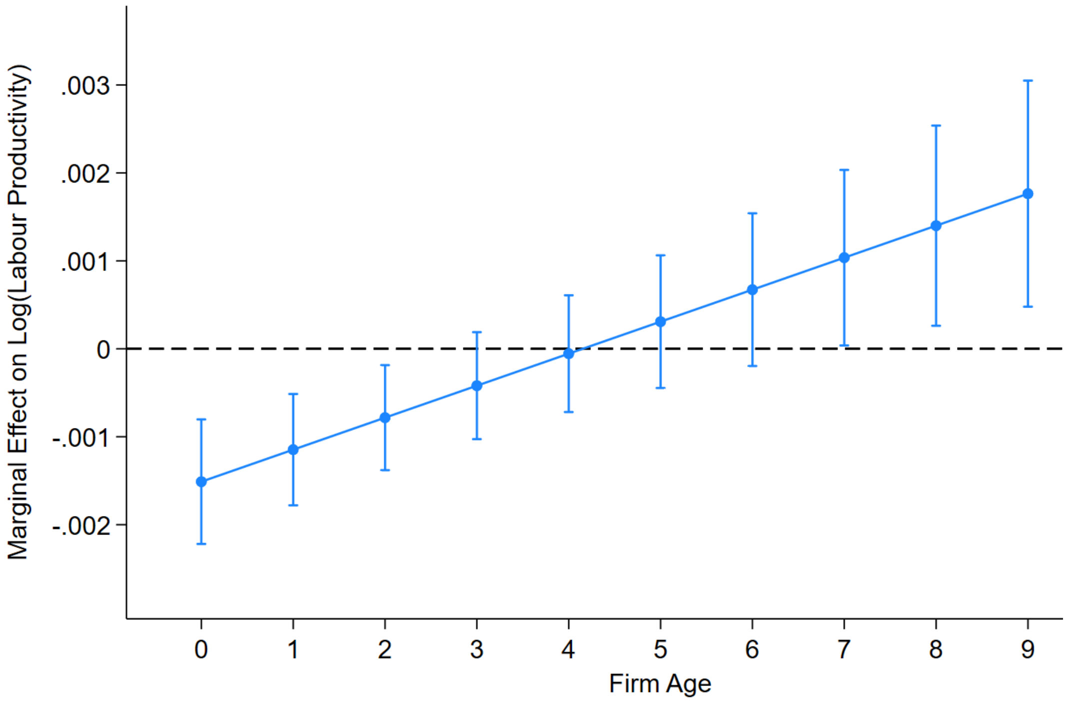

Figure 4.A.8 - Marginal effect of the percentage of employees coming from large firms (more than 20 employees) on Log (labour productivity), across firm age, not including weights for inverse probability of survival.

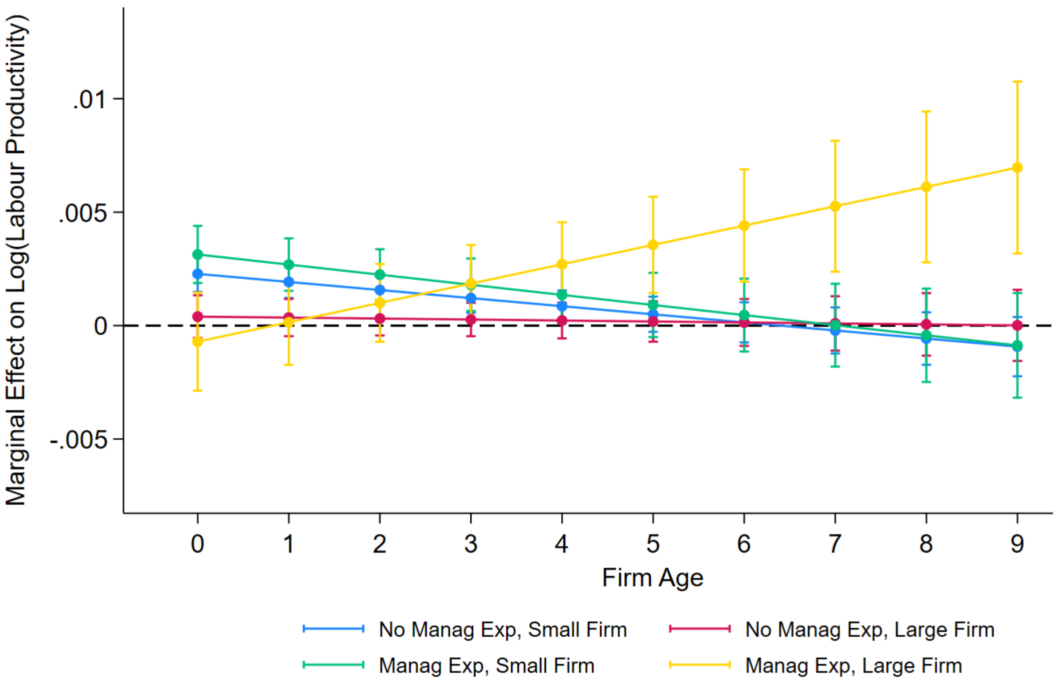

Figure 4.A.9 - Marginal effects of employees categories on Log (labour productivity), across firm age, not including weights for inverse probability of survival.

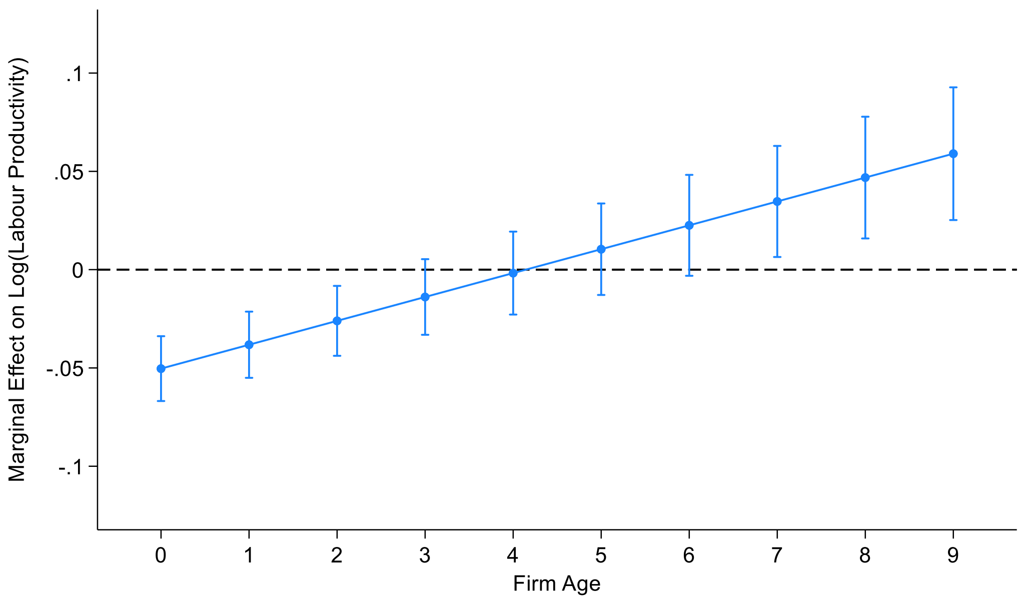

Figure 4.A.10 - Marginal effects of founder's prior firm size on Log (labour productivity), across firm age, including worker fixed effects.

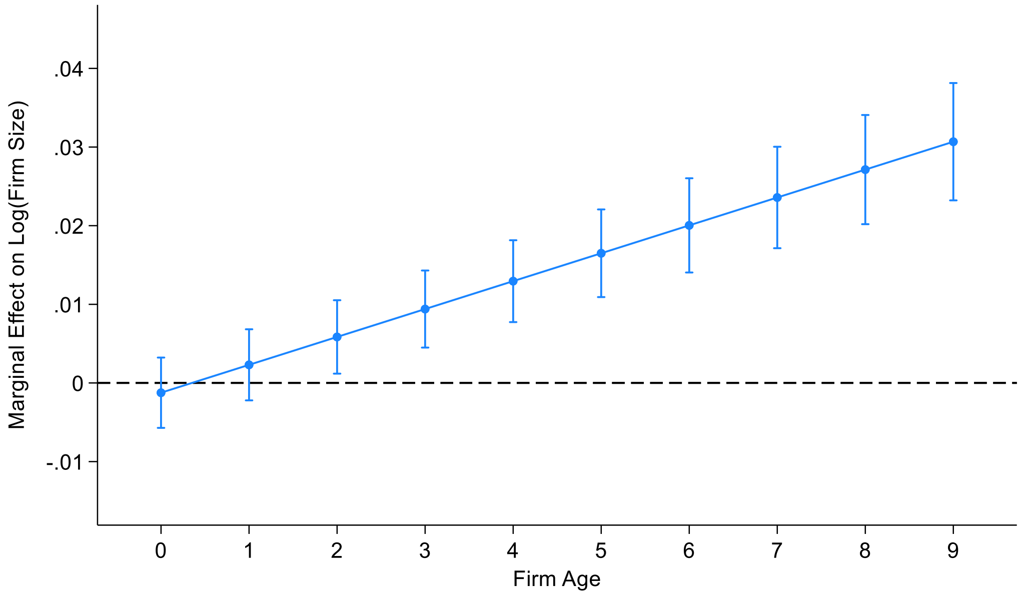

Figure 4.A.11 - Marginal effects of founder's prior firm size on Log (firm size), across firm age, including worker fixed effects.

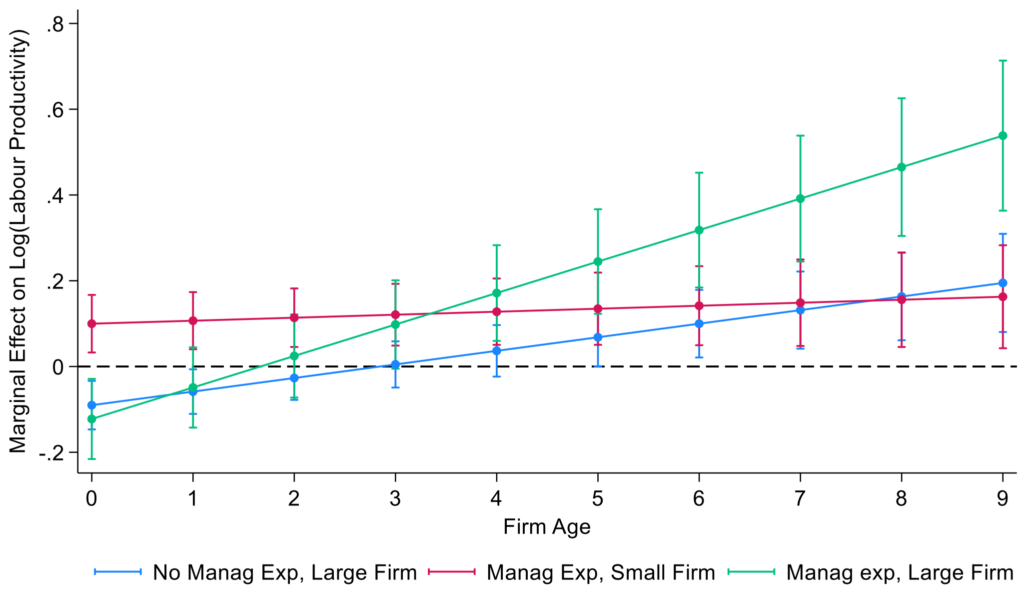

Figure 4.A.12 - Marginal effects of startup's founder's category on Log (labour productivity), across firm age, including worker fixed effects.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

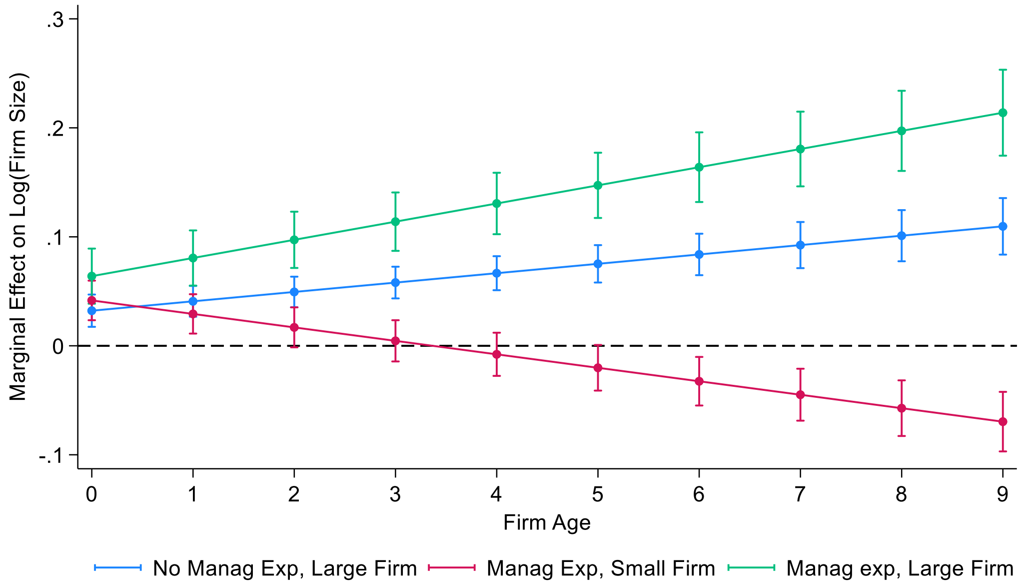

Figure 4.A.13 - Marginal effects of startup's founder's category on Log (firm size), across firm age, including worker fixed effects.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

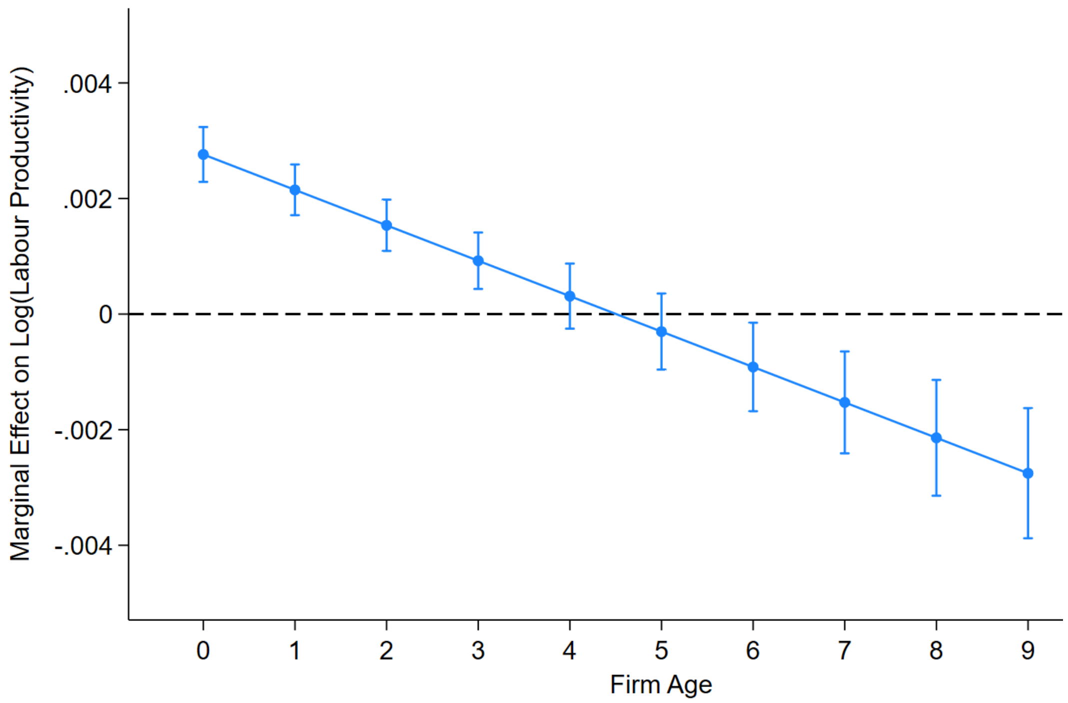

Figure 4.A.14 - Marginal effect of the percentage of employees coming from small firms (with 20 or less employees) on Log (labour productivity), across firm age, including worker fixed effects.

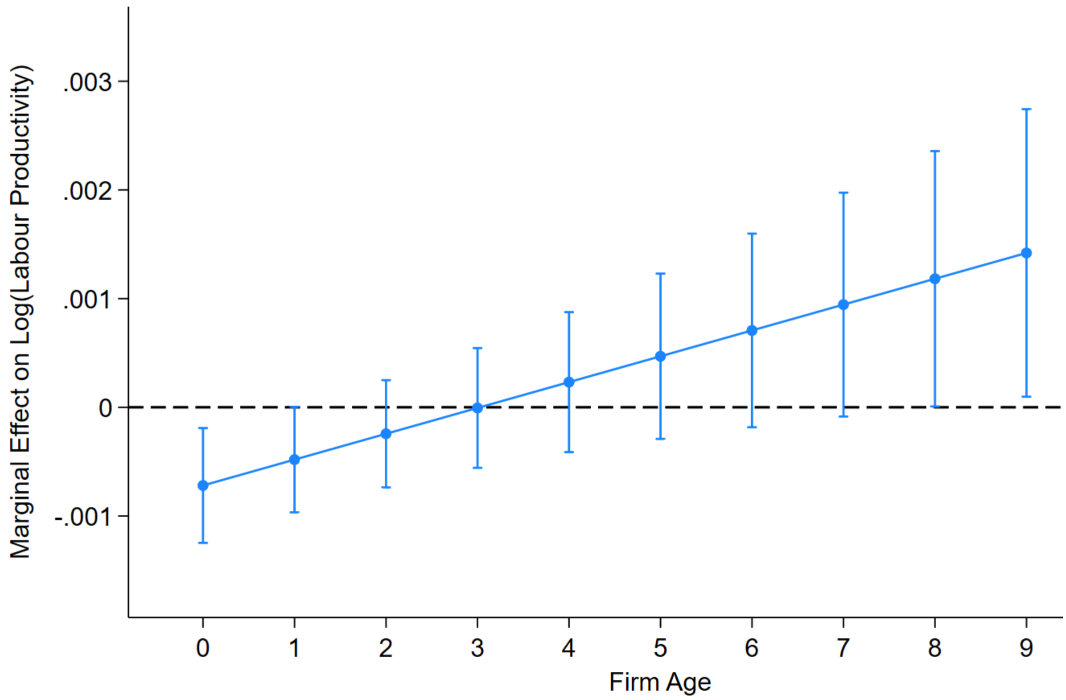

Figure 4.A.15 - Marginal effect of the percentage of employees coming from large firms (more than 20 employees) on Log (labour productivity), across firm age, including worker fixed effects.

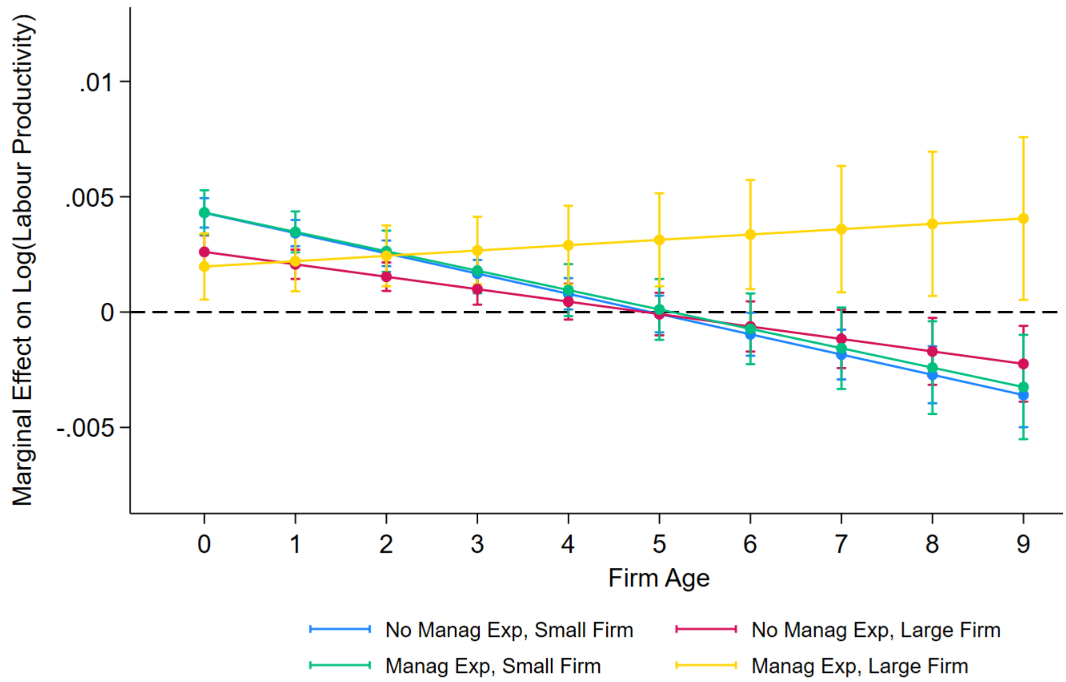

Figure 4.A.16 - Marginal effects of employees categories on Log (labour productivity), across firm age, including worker fixed effects.

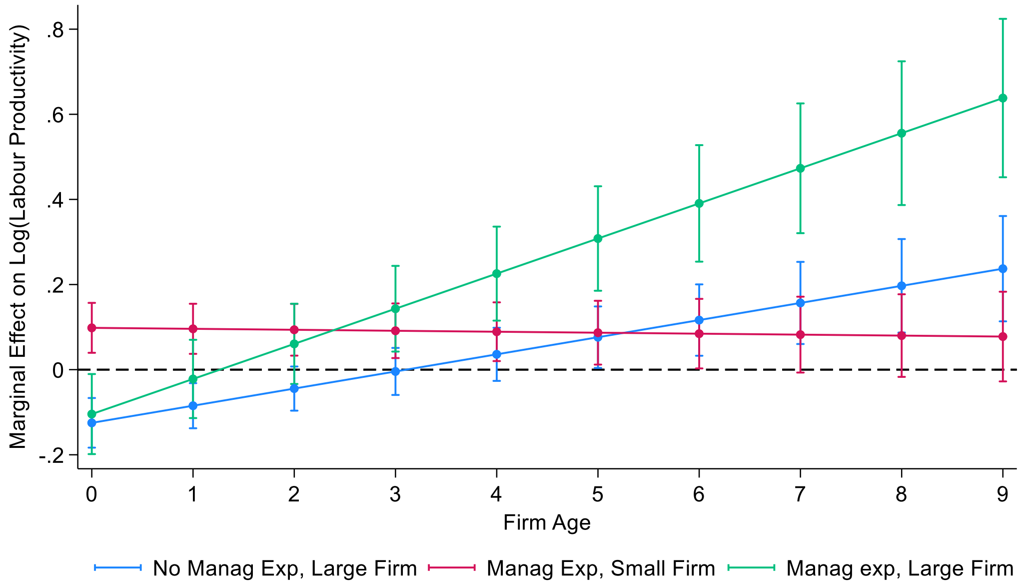

Figure 4.A.17 - Marginal effects of startup's founder's category on Log (labour productivity), across firm age, using alternative measures for small and large firms.

Notes: Past firm size small for firms with 50 or less employees. Past firm size large for firms with more than 50 employees.

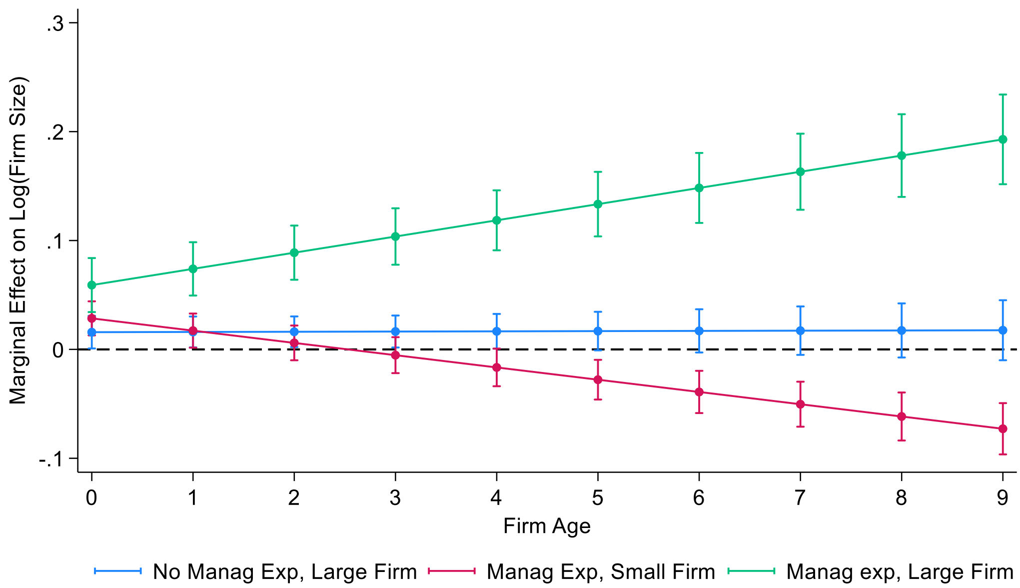

Figure 4.A.18 - Marginal effects of startup's founder's category on Log (firm size), across firm age, using alternative measures for small and large firms.

Notes: Past firm size small for firms with 50 or less employees. Past firm size large for firms with more than 50 employees.

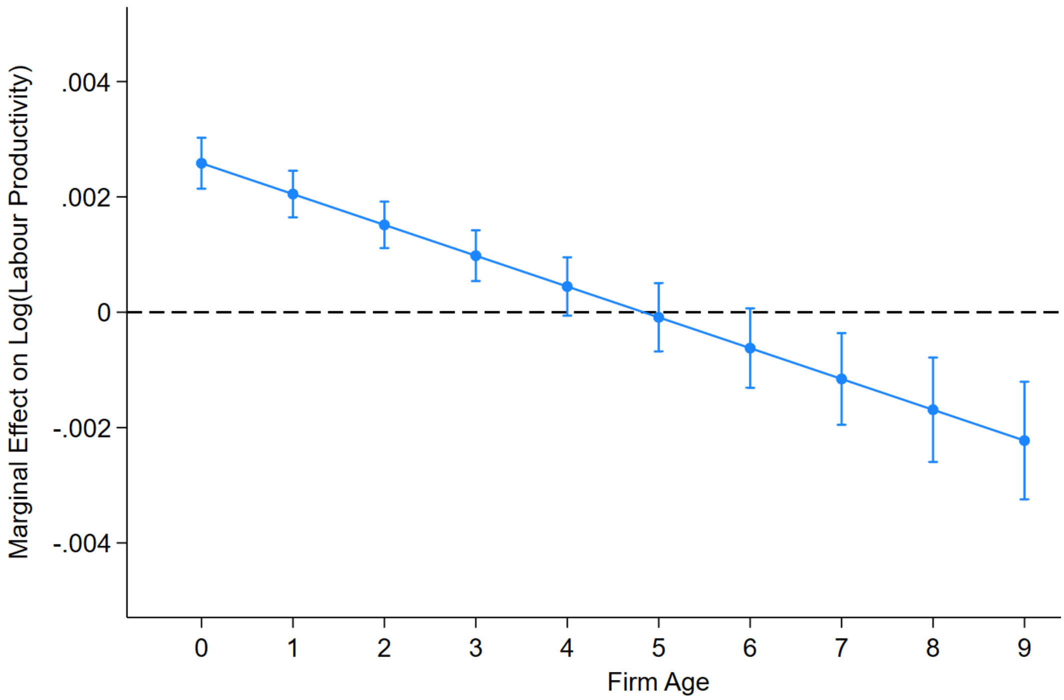

Figure 4.A.19 - Marginal effect of the percentage of employees coming from small firms (with 50 or less employees) on Log (labour productivity), across firm age, using alternative measures for small and large firms.

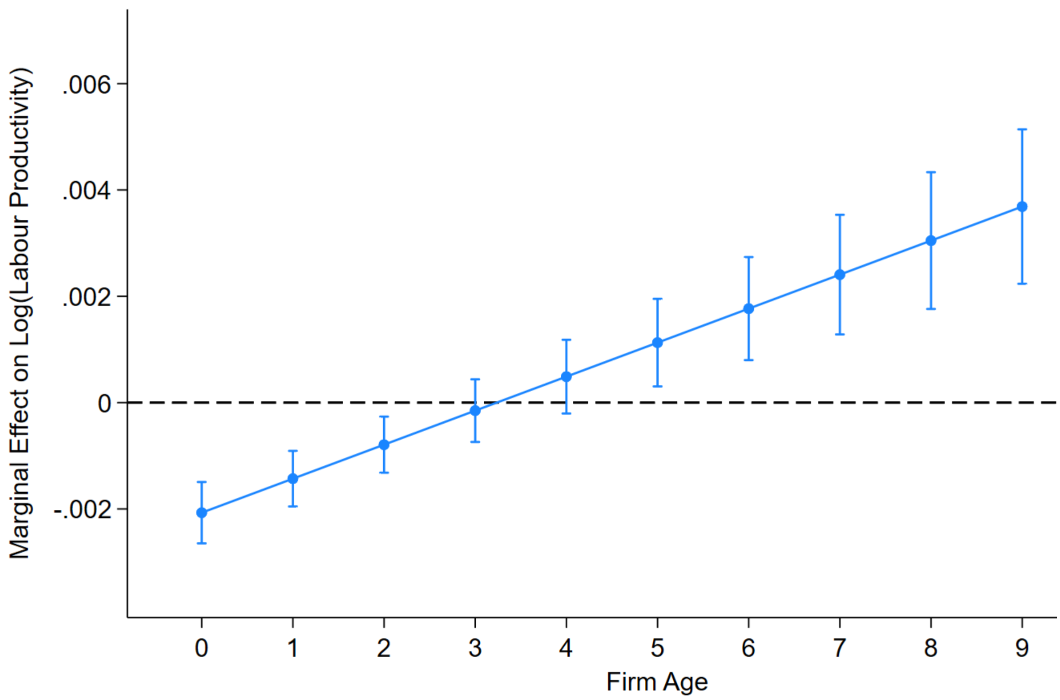

Figure 4.A.20 - Marginal effect of the percentage of employees coming from large firms (more than 50 employees) on Log (labour productivity), across firm age, using alternative measures for small and large firms.

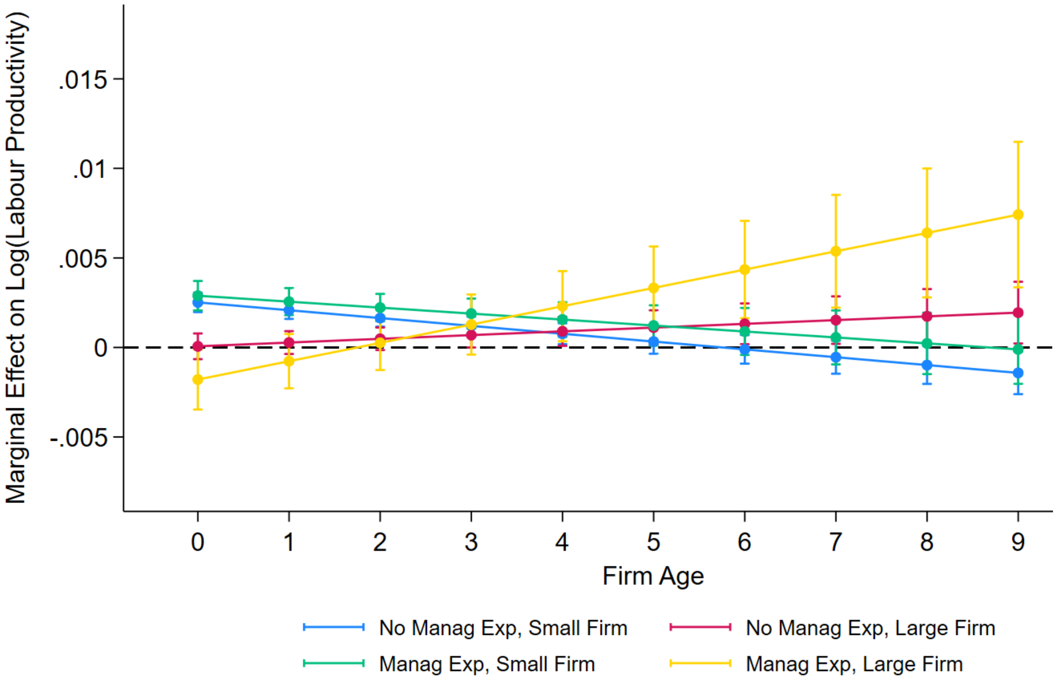

Figure 4.A.21 - Marginal effects of employees categories on Log (labour productivity), across firm age, using alternative measures for small and large firms.

Notes: Past firm size small for firms with 50 or less employees. Past firm size large for firms with more than 50 employees.

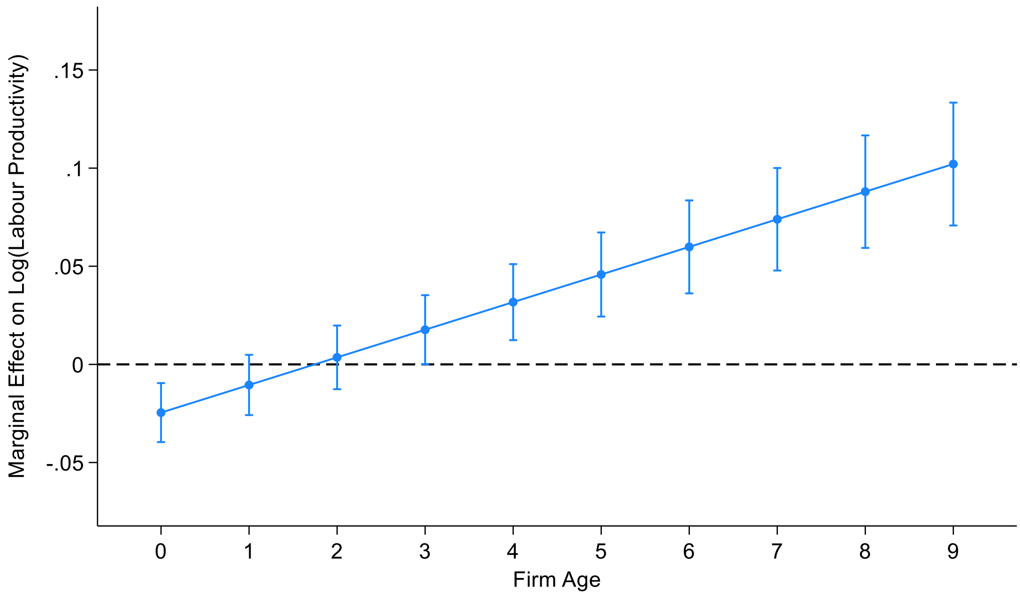

Figure 4.A.22 - Marginal effects of founder's prior firm size on Log (labour productivity), across firm age, excluding firms without any of its original founders.

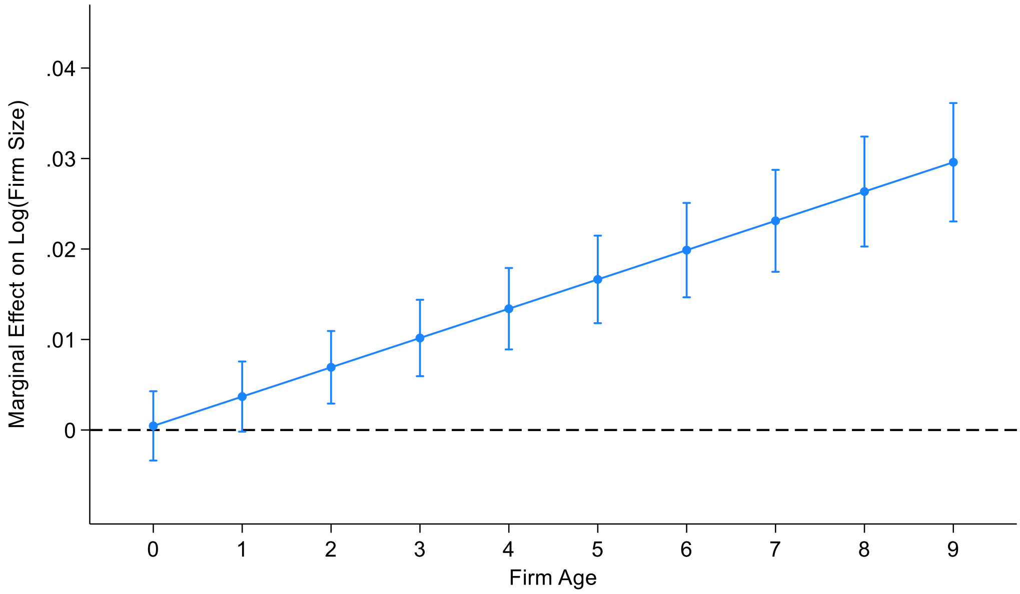

Figure 4.A.23 - Marginal effects of founder's prior firm size on Log (firm size), across firm age, excluding firms without any of its original founders.

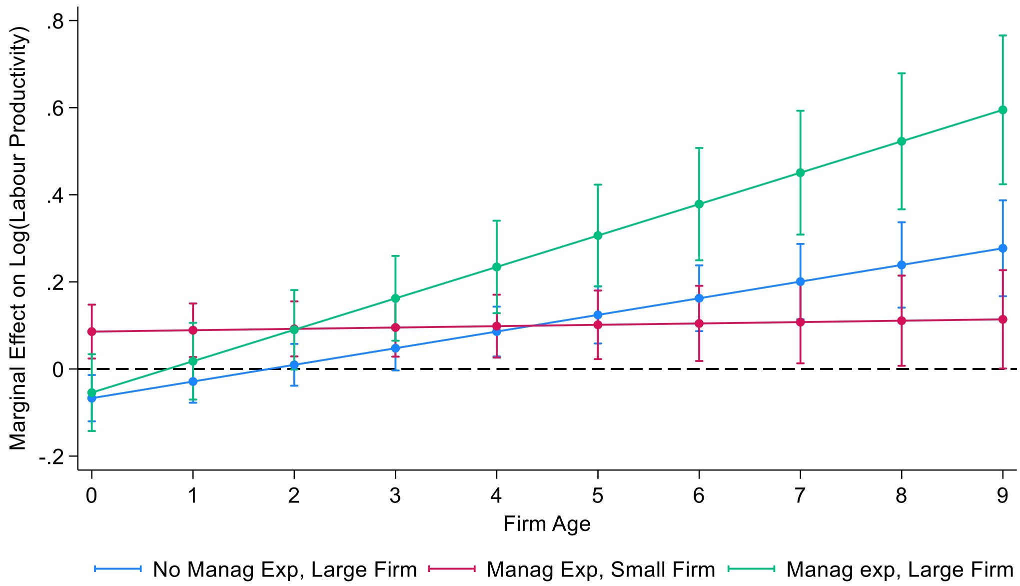

Figure 4.A.24 - Marginal effects of startup's founder's category on Log (labour productivity), across firm age, excluding firms without any of its original founders.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

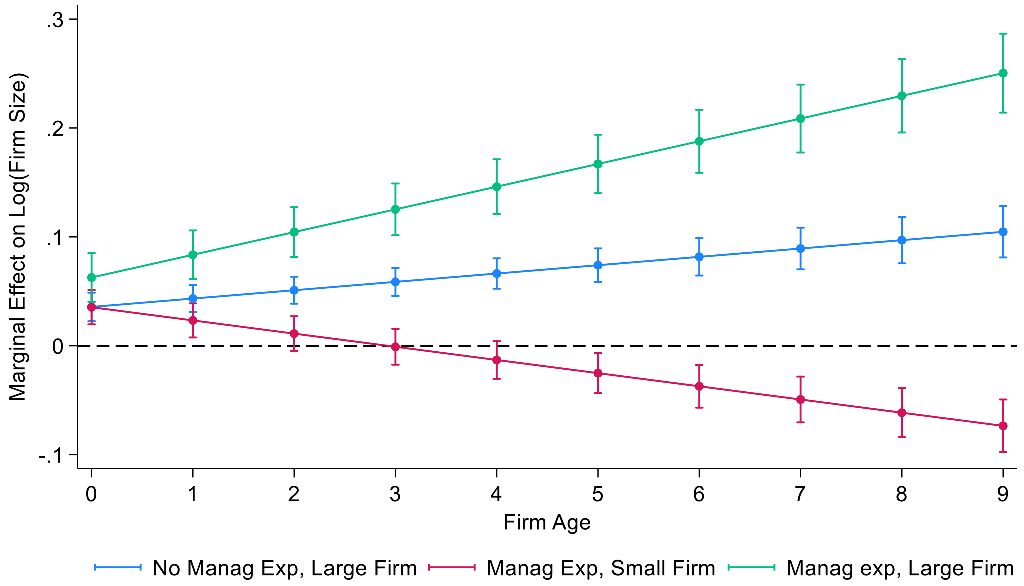

Figure 4.A.25 - Marginal effects of startup's founder's category on Log (firm size), across firm age, excluding firms without any of its original founders.

Notes: Past firm size small for firms with 20 or less employees. Past firm size large for firms with more than 20 employees.

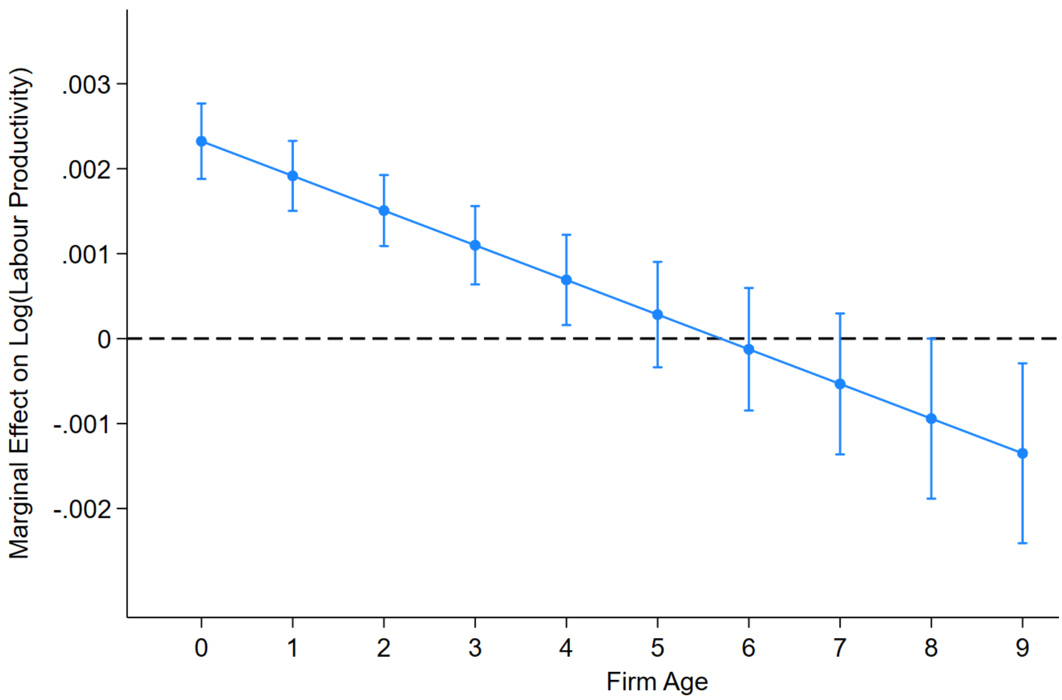

Figure 4.A.26 - Marginal effect of the percentage of employees coming from small firms (with 20 or less employees) on Log (labour productivity), across firm age, excluding firms without any of its original founders.

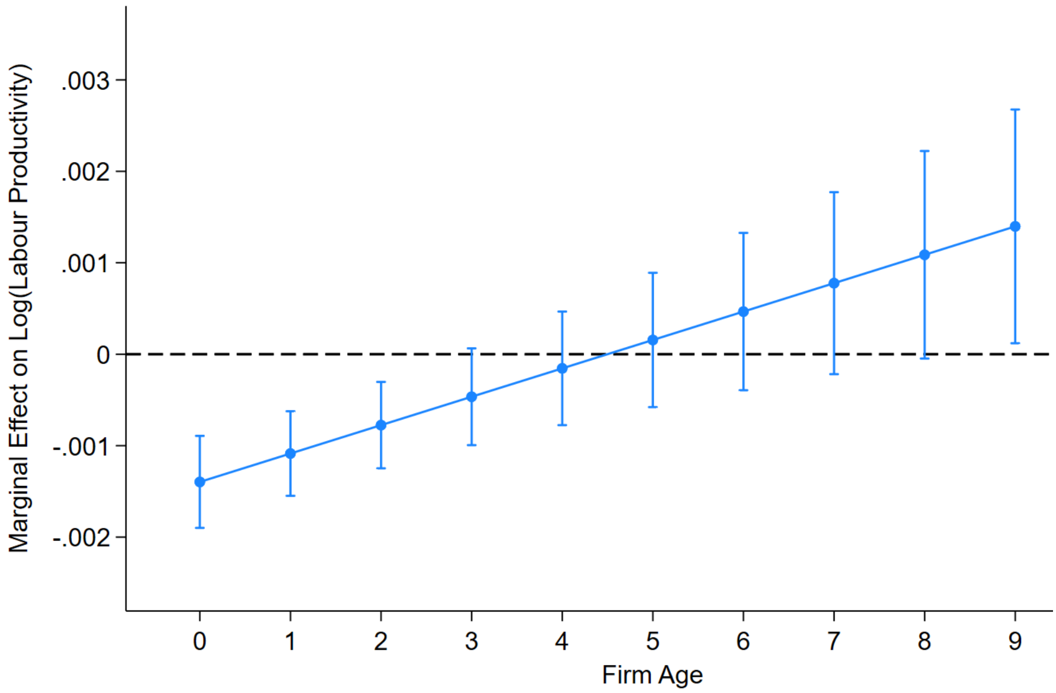

Figure 4.A.27 - Marginal effect of the percentage of employees coming from large firms (more than 20 employees) on Log (labour productivity), across firm age, excluding firms without any of its original founders.

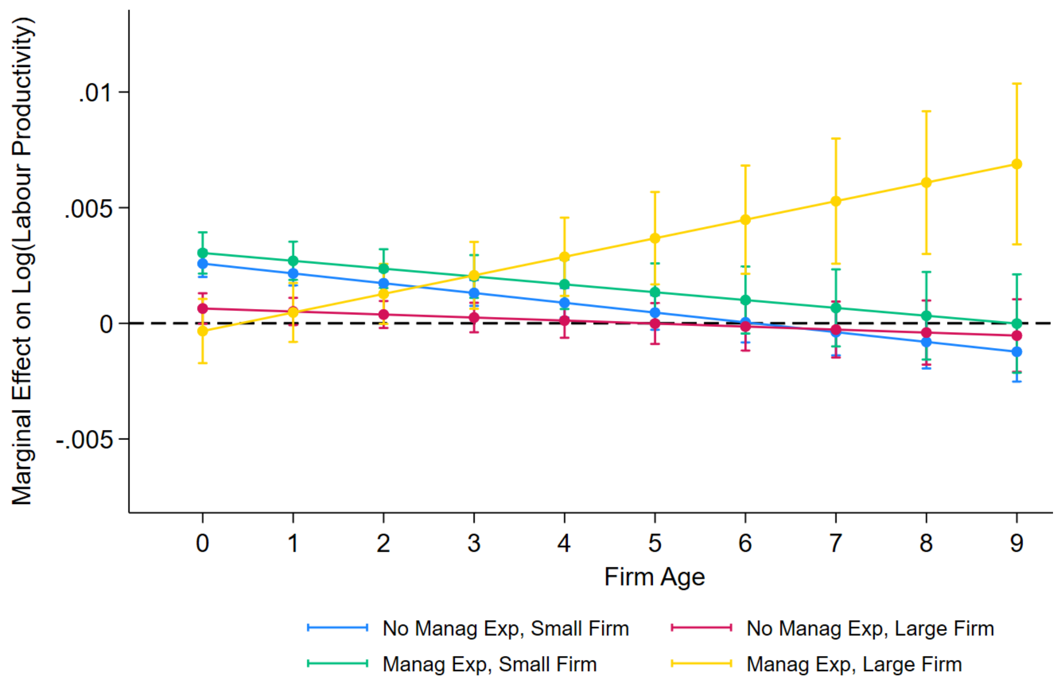

Figure 4.A.28 - Marginal effects of employees categories on Log (labour productivity), across firm age, excluding firms without any of its original founders.

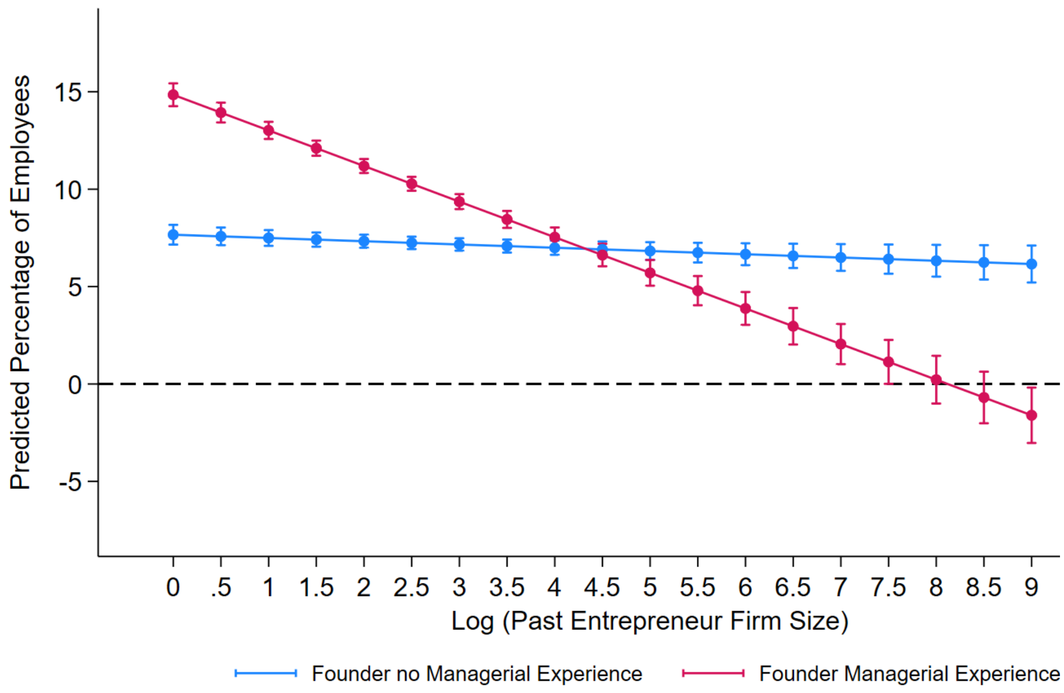

Table 4.A.29 - Marginal effects of founder's previous firm size and managerial experience on the percentage of employees with managerial experience coming from small firms.

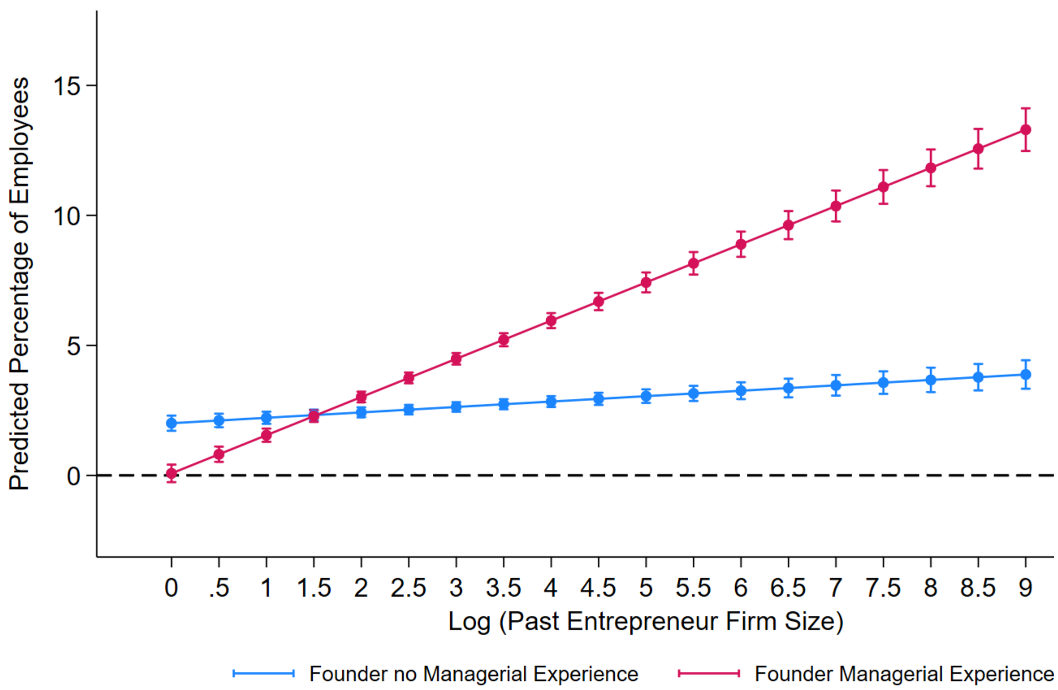

Table 4.A.30 - Marginal effects of founder's previous firm size and managerial experience on the percentage of employees with managerial experience coming from large firms.

Chapter 5

Final Remarks

In this dissertation, we analysed how firm characteristics and workforce demographics impact both the likelihood of entrepreneurial transitions and entrepreneurial outcomes, focusing especially on the roles of age, managerial experience, and firm size. Using a detailed matched employer-employee dataset from Portugal, we provided econometric findings that complement past theories on the predictors of entrepreneurial transitions and startup performance, namely when it comes to the rank effect and the small firm effect.

In Chapter 2, we examined the career paths that are more likely to lead workers to become business owners. Using sequence analysis, we analysed individuals who eventually transition into business ownership, over a 10-year period, constructing clusters of similar career paths. Our results highlight that obtaining experience as a manager is positively linked with entrepreneurial transitions. Moreover, our findings suggest that working in firms in which managers are younger, and in which workers reach managerial positions at younger ages, is also a common path to entrepreneurship. We also show that managers, who are more likely to become business owners, worked in smaller firms than non-managers, in accordance with the small firm effect. The results of these analyses served as a powerful descriptive tool of the career paths that are commonly related with entrepreneurial transitions, having served as a foundation to the econometric analyses carried out in Chapters 3 and 4.

Chapter 3 analysed the mechanisms behind the rank effect in detail. In this study, we investigated if the demographic characteristics of firms' managers impact the career progression of workers occupying lower positions in the firm, and if, in turn, workers facing delayed career progression exhibit lower entrepreneurial propensities. Using discrete-time hazard models, we show that the presence of older managers within firms lowers the likelihood of managerial promotions for younger and less experienced employees, lowering their likelihood of becoming entrepreneurs. Furthermore, we highlight that workers facing delayed or impeded career progression are more likely to move to other firms as paid employees, but not more likely to transition into entrepreneurship. We also investigated differences between top and middle managers, finding that top managers transition into entrepreneurship at higher rates than middle managers, but are less likely to move to other firms as wage workers. By zooming in on the impact that the managerial workforce has on delayed career progression and entrepreneurial propensities of the workforce, this study provided support for the rank effect theory, further extending the findings of past literature.

Finally, in Chapter 4 we analysed not entrepreneurial transitions, but rather startup performance. Based on past findings from both the rank effect and small firm effect theories, we examined how past work experiences of startups' founders and employees, particularly their past managerial experience and the size of their previous firms, impacts startup success. Our results suggest these relationships change as startups age: in the early stages, startups founded by individuals from small firms, and those that initially hire employees e from small firms, are the better performing in the sample. However, as startups mature, larger firm experience, especially when paired with managerial experience, becomes a stronger predictor of increasing performance. These results indicate that different skillsets become critical at different stages in a startup's life cycle.

The findings of this dissertation show a nuanced picture of how firm characteristics and work experience impact workers' entrepreneurial propensities and the performance of newly created firms. On one hand, obtaining managerial experience is a strong predictor of entrepreneurial transitions and of positive startup performance. This suggests that easing the promotion of workers into managerial roles could lead to higher entrepreneurial rates, and to the creation of successful startups. However, if managers hold onto their positions for long periods of time, the presence of such older and more experienced managers within firms will delay the career progression of younger workers into managerial positions, potentially lowering their chances of creating their own firms. As such, ideally, promotions into managerial positions should happen while workers are still young, allowing them to accumulate relevant experience while still at an age in which they are likely to venture into entrepreneurship.

Moreover, we find nuanced results when analysing the impact that firm size has in these relationships. We show that employees of small firms are more likely to become entrepreneurs, and that small firm experience is connected with early entrepreneurial success. However, experience in larger firms becomes increasingly valuable as startups grow, suggesting that the most successful startups are those created by the employees who are less likely to transition to entrepreneurship.

We hope the results shown in this dissertation contribute to the literature on the relationship between workforce demographics, work experience, and the propensity of entrepreneurial transitions and subsequent startup performance, stimulating further research in these fields.

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