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Author
Denislamova, Olga

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Essays in Macroeconomics

A dissertation submitted in partial satisfaction of the
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Olga Denislamova

Committee in charge:

Professor David Lagakos, Co-Chair
Professor Marc Muendler, Co-Chair
Professor Tital Alon
Professor Ruixue Jia
Professor Munseob Lee

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The dissertation of Olga Denislamova is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

University of California San Diego

2021

DEDICATION

To my grandmother Olga, my mother Irina and my sister Diana,

the most inspiring women I know.

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I am grateful to a great number of people who supported me through my graduate studies.

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VITA

2014	M.A. in Economics & Politics, University of Edinburgh, UK
2016	M.A. in Economics, University of California San Diego, USA
2021	Ph.D. in Economics, University of California San Diego, USA

ABSTRACT OF THE DISSERTATION

Essays in Macroeconomics

by

Olga Denislamova

Doctor of Philosophy in Economics

University of California San Diego, 2021

Professor David Lagakos, Co-Chair
Professor Marc Muendler, Co-Chair

This dissertation consists of three chapters that discuss the evolution of the skill composition of the workforce in firms, as well as in municipal governments.

Chapter 1 connects firms' demand for skilled labor to their need to invest in organizational capital, a type of intangible capital. I develop a firm dynamics model of endogenous organizational capital accumulation which I use to measure firms' investment in organizational capital and explore the role of organizational capital in firm growth. Using Brazilian administrative data, I study the life cycle demand for skilled labor by high-performing firms in Brazil and find that the share of skilled workers in such firms decreases with age. I use this fact to

discipline my model and find that high-performing firms spend 25% of their total wage bill on organizational capital investment and that the accumulation of organizational capital across the firm's life cycle generates 28% of its total growth.

In Chapter 2, I examine what happens to the average wages as firms expand and find that as firms grow, the average wages in the firm fall. I identify that the average wage decrease is mostly due to the change in the worker composition of the firm towards a less skilled workforce. I find that the change in the composition happens mostly via firm hiring, with firms disproportionately hiring lower skilled workers as they grow.

In Chapter 3, I examine whether the overall competence level of municipal workers changes after the municipality is audited and revealed to be corrupt. I take advantage of the random audits of the municipal governments' use of federal funds in Brazil and find that in municipalities that are revealed to be corrupt there is an increase in the overall competence level of the municipal workers following the audit. I find that the effect is mostly driven by the change in the competence level of new hires, which I interpret as evidence that the exposure of corruption serves as a temporary deterrent for future administrations to use public sector employment as a reward for their political supporters.

Chapter 1

Firm Growth, Worker Skill Composition and Organizational Capital

1.1 Introduction

Since Marshall (1961), there has been a recognition in the literature that there is a type of capital, separate from physical or human capital, that firms require in order to operate and that they acquire throughout their life cycle. A large umbrella term for this kind of capital is intangible or knowledge-based capital (KBC). Corrado and Hulten (2010) show that the share of intangible capital, broadly speaking, in overall business investment has been increasing steadily since the 1950s in many developed countries, and in some cases (such as the UK and the US) has recently exceeded investment in tangible capital. Given such shift in its importance, there has been an increase in interest towards different types of intangible capital and investment into it. In economics, the most studied type of KBC investment has been Research & Development (R&D) expenditure. The relative conceptual ease of R&D expenditure measurement and its immediate theoretical link to firm performance meant that it has been studied widely over the last twenty years, as shown in a review by Hall (2010) Hall and Rosenberg (2010). However, together with the increase in the investment into R&D over the last decades, there has also been an increase in expenditure on other types of knowledge assets (Corrado et al. 2005,2009), which have been left relatively unexplored in the economics literature, even though they have gathered a fair share of attention in the business literature. This paper focuses on one such type of knowledge-based capital, organizational capital, and proposes a model that connects organizational capital to firm growth and within-firm worker skill composition across the firm's life cycle. The contribution of this paper is twofold. Firstly, I propose a simple model that incorporates organizational capital into the firm's production function and provides a quantitative assessment of how much firm growth originates from organizational capital accumulation. Secondly, I document a novel empirical fact that the average level of skill within a firm declines as firms age, which I use to calibrate the model. This allows me to circumvent known measurement issues in the organizational capital literature and estimate that high-performing firms spend 25% of their total wage bill on organizational capital investment and 28% of firm growth stems from organizational capital accumulation.

Organizational capital is, perhaps, the most nebulous type of KBC, illustrated by the numerous definitions of organizational capital presented in the business and economics literature. The broad definition of organizational capital is that it is part of the organization's stock of knowledge that comprises its core competences, is often non-imitable and firm-specific and generates sustained competitive advantage. Importantly, this knowledge has to be somehow embedded or institutionalized in the firm's systems and processes, whether explicitly or tacitly (Nonaka (1994)). Gomes (2007) gives a more precise definition of organizational capital being the firm's codified and tacit knowledge about itself and its environment: standards, production procedures, "codes, technical languages, practical arrangements about how the work is done and the creation of an organizational culture". In economics literature, organizational capital is often defined as firm-specific knowledge that affects what and how successfully the firm is able to produce. For example, Evenson and Westphal (1995) define organizational capital as "the knowledge used to combine human skills and physical capital into systems for producing and delivering want-satisfying products", whereas Prescott and Visscher (1980) define organizational capital as a type of firm knowledge that can affect the firm's production possibility set. The various definitions that exist (outlined in more detail below) all emphasize that organizational capital is a knowledge asset that is firm-specific, is tasked with linking tangible and intangible assets and is of great strategic importance.

A big challenge in the organizational capital literature has been the issue of measuring organizational capital in a way that is consistent and comparable across different firms and different countries. Without a consistent way to measure organizational capital, it is difficult to convincingly quantify its importance for firm's performance or study ways in which firms could better accumulate it, if it is indeed strategically important. The core of the measurement issue is apparent from the common threads in the definitions of organizational capital: it being firm-specific explicitly codified and tacit knowledge that gives firms a sustained competitive edge. According to that definition, no two firms with high stock of organizational capital should look alike. Given the virtual impossibility of direct measurement of organizational capital, many proxies have been used in its place. Common approaches include using selling, general and administrative (SGA) expenditure as a proxy for investment into organizational capital (Eisfeldt and Papanikolaou (2013)) or relying on managerial compensation (Corrado et al. (2009b)), which have the tendency to either overestimate or underestimate the amount or organizational capital investment in the firm. More recently, Mouel and Squicciarini (2015) have been using a task-based approach by explicitly quantifying which occupations routinely perform tasks that affect the medium and long-term functioning of the firm, which they relate to increasing the firm's stock of organizational capital. Importantly, they show that workers who engage in organizational capital accumulation tend to be high-skilled, which I use in my approach to quantifying the importance of organizational capital for firms' performance, as I explicitly link organizational capital accumulation to the share of skilled workers in the firm's workforce.

In this paper, I outline a method of assessing the importance of organizational capital accumulation for firm performance while circumventing the need to directly measure the stock of organizational capital in each firm by developing and calibrating a model of endogenous organizational capital accumulation. I propose a Hopenhayn (1992) type model of industry dynamics in which organizational capital is necessary for production and is the driving force behind endogenous firm growth. In this respect, the mechanism is similar to a model outlined in Bloom et al. (2016) where they use managerial capital as a direct input into production. I model organizational capital as a firm-specific resource that cannot be sold or bought in the market and that is completely lost once the particular firm exits the market. Based on insights from the business literature (discussed in more detail below), I assume that only skilled workers can perform tasks that lead to the accumulation of organizational capital, which is then used in production just like any input. I allow organizational capital to partially depreciate, which is a familiar idea in the literature on organizational capital (Corrado et al. (2005, 2009)), based on the logic that regardless of what procedures and structures the firm comes up with at the beginning of its life cycle, they will become outdated as the firm ages and the economy around the firm changes. I assume that there are diminishing returns to investing in organizational capital using the skilled labor input.

This model formalizes the following intuition behind firm's growth. When a firm enters the market, it does so with an idea for a product or a service. However, going from an idea to production and sales takes not only hiring workers and accumulating necessary physical capital, but also coming up with a structure of the production process, standards and procedures that need to be codified in order to be replicated later on should they turn out to be successful. This process takes time as well as input from skilled labor. Only once the firm has come up with production procedures and standards, i.e. accumulated sufficient organizational capital, can it expand by replicating the successful strategy. Given the difficulties associated with directly measuring organizational capital, the stock of strategies and firm-specific knowledge that the firm needs to grow, I use an indirect approach to calibrate the model. I find a novel empirical fact that both in the cross-section and throughout the firm's life cycle, older firms have proportionately fewer skilled workers. I use this fact to identify the parameter that describes the diminishing returns to investment in organizational capital. I then calibrate the model to the Brazilian economy using data from the RAIS matched employer-employee dataset and use the calibrated model to estimate that high-performing firms spend 25% of their total wage bill on organizational capital investment and 28% of total firm growth can be attributed to organizational capital accumulation.

This paper contributes to the literature that explicitly models knowledge based capital as part of the firm's production process. Prescott and Visscher (1980) describe organizational capital as a particular kind of information in the firm, mostly with regard to the best way to separate workers into teams and matching workers with different tasks, which is produced jointly with output. They use the model to embellish the theory of adjustment costs and justify why firms would choose to grow slowly and adjust their labor gradually by introducing the accumulation of organizational capital, so their model addresses a different question. Prescott and Visscher (1980) state that if a firm wants to grow without disproportional increases in operating costs, it needs to grow its information stock - organizational capital, alluding to its importance for firm growth, which I aim to quantify in this paper. Bloom et al. (2016) include managerial capital into the firm's production function and find that differences in managerial practices account for 30% of total factor productivity differences across countries and across firms within countries. The paper that is most relevant to this work is the paper by Atkeson and Kehoe (2005) . They also argue that organizational capital is the driving force behind firm growth and propose a model where firms differ in the vintage of technology and can accumulate organizational capital as they age. They use the model to quantify the amounts of organizational rents that accrue to firm owners that have to be compensated for waiting for their firms to accumulate organizational capital and grow. On average, they estimate that around 40% of all payments to intangible capital are payments to organizational capital (with the payments to intangible capital making around

8% of U.S. total manufacturing output). The main difference between our papers, besides the questions that we set out to answer, is the the organizational capital accumulation process is an exogenous stochastic process in their model, whereas I endogenize it by explicitly modeling the link between skilled labor and organizational capital. This allows me to use the change in the firm skill composition with age to calibrate my model.

The paper also contributes to the literatures that set to quantify how much firms invest in organizational capital and what effects it has on firms' performance. Eisfeldt and Papanikolaou (2013) find that firms that invest more in organizational capital are more productive, have higher risk-adjusted returns and offer higher executive compensation. Lev et al. (2009) also find that firms with higher levels of organizational capital have higher long-term operating and stock performance. I find that firms devote approximately 25% of their total wage bill towards investment in organizational capital and that around 28% of firm growth is generated by organizational capital.

The paper proceeds as follows. Section 2 describes in more detail the notion of organizational capital, how it can be measured and how it is connected to skilled labor. Section 3 outlines the theoretical framework and the numerical method for estimating the model. Sections 4 and 5 describe the data and the empirical results used to calibrate the model. Section 6 presents model fit and discusses to what extent the mechanism of accumulating organizational capital can account for firm growth. Finally, Section 7 concludes.

1.2 Organizational Capital

1.2.1 Defining organizational capital

Organizational capital is a nebulous concept, and it does not have a precise agreed upon definition in the literature. There is consensus that it represents some type of knowledge that is firm-specific, accumulated throughout its lifetime and is necessary for firm's success, but it is the particular type of information that is included in the definition of organizational capital that scholars disagree on, as well as where organizational capital resides. Even though it has proven to be difficult to formally define what organizational capital is, it is possible to see the presence of this tacit firm knowledge and the importance of skilled labor in accumulating it in examples from the business world case studies. Consider the story of Willow Run, the factory owned and constructed by the Ford Motor Company, designed for the purpose of mass-producing B-24 Liberators during World War II. The first blue prints of a factory that would house the production were famously drawn out on Coronado Hotel place mats overnight in April 1941 by Ford production chief Charles Sorensen, and were approved by Ford management the next morning. At the end of 1941 a massive factory was complete and began producing parts immediately upon construction. However, the first planes were mass-produced only in the last weeks of 1942, and even then they were deemed unfit for battle and used at training camps instead. Only in mid 1944 was the coveted one plane per hour production rate achieved.

Why did it take so long to begin producing at a rate and cost that were desirable? The factory was mostly ready within nine months, and even though there was significant shortage of labor throughout its operation, these were not the main bottlenecks. The main bottleneck was adjusting the assembly process from producing cars to producing planes, figuring out what should be done in-house and what needs to be outsourced to keep the costs under control and production efficient. When the venture was started, Ford Motor Company had a lot of organizational capital that was appropriate for car production, and very little organizational capital that was useful for building planes. At the beginning of the venture, Sorensen worked closely with several large teams of engineers, draftsmen, managers and accountants who were coming up with blue prints for the production process and cost calculations in an attempt to find the perfect formula for the plane to be produced quickly and cheaply. They were accumulating organizational capital. The process was further complicated by the fact that government requirements for what the Liberator was meant to be able to achieve changed constantly, informed by the lessons from the fighting fronts. After each change in regulations, Ford Motors Company had to re-optimize its business and manufacturing model, eventually settling on outsourcing some parts of production. Once this was figured out though, Willow Run reached its peak productivity, when it employed 40,000 employees, many of them previously unskilled workers who went through appropriate training at the Aircraft Apprentice School that was build on the premises of Willow Run for this very purpose. The accumulation of organizational capital was accompanied with an increase in production and a shift in the workforce composition, where low-skilled workers could follow the process outlined for them by high-skilled workers and embodied in organizational capital: codified and tacit knowledge that is specific to the firm.

There are two main themes that run through most definitions of organizational capital: that it represents firm-specific knowledge that is essential to the firm's success and that it is embedded both in the firm's workforce and in the firm itself. Lev et al. (2009) refer to organizational capital as 'the mother of intangible assets" (Lev et al. (2009).) and define it as the "the agglomeration of business processes and systems, as well as a unique corporate culture, that enables firms to convert factors of production into output more efficiently than competitors". They state that the role of organizational capital is to provide companies with the ability to systematically outperform their competitors and that it remains in the organization even if the key individuals leave. Wright et al. (2001) and Youndt et al. (2004) define organizational capital as knowledge accumulated by and contained within the firm, institutionalized in its organization processes and databases, documents, patents and manuals that facilitate the firm's ability to store knowledge. Carlin et al. (2012) define organizational capital as a form of intra-firm language, which "summarizes informal work routines, convenient technical jargons, and a vocabulary of patterns remembered from past experiences", hence indicating that it is indivisible from the firm. On the other hand, Eisfeldt and Papanikolaou (2013) define organizational capital as a form of durable intangible capital that is partly firm specific and that is embodied in the employees of the firm, so can be partly movable across organizations. The work by Mouel and Squicciarini

(2015) described in greater detail below, also subscribes to this view.

In the economics literature, Prescott and Visscher (1980) define organizational capital as mainly the information about personnel, such as the human capital of the workers, what teams they are best sorted into and what tasks they are best suited for. Atkeson and Kehoe (2005) state that organizational capital is the driving force behind firm growth and propose a model where firms differ in the vintage of technology and accumulate organizational capital as they age. Other papers, such as Jovanovic and Moffitt (1990) or Topel (1991) do not explicitly talk about organizational capital, but speak of the time that it takes to find out the quality of a match between the firm and the worker and the great value associated with this knowledge. There are also other papers that do not explicitly refer to organizational capital, but nonetheless study issues very much related to it. In macroeconomics, models that model firm growth as coming from endogenous learning by doing such as as Rosen (1972) fall in this category. Learning-by-doing as a source of growth can be conceptualized as the firm accumulating firm-specific knowledge about its competitive advantage - organizational capital.

It is important to note that organizational capital is considered to be different from pure R&D investment and from managerial capital, even though some aspects of these concepts overlap. R&D includes innovative activities geared towards development of new goods and services. Organizational capital represents the integration of the knowledge sometimes gathered from R&D activities into routines that become an integral part of the firm's future actions. With regards to its similarity with management capital, it is indeed true that a large part of organizational capital accumulation is performed by managers. Mouel and Squicciarini (2015) perform a task-based analysis of various occupations in the firm using the OECD Programme for the International Assessment of Adult Competencies (PIAAC) database in order to see which occupations contribute to organizational capital accumulation. They define organizational capital as the "firm-specific organizational knowledge resulting from the performance of tasks affecting the long-term functioning of firms." Based on this definition, they come up with a set of tasks that they believe fall under activities aimed at affecting the long-term function of the firm, such as developing objectives and strategies; organizing, planning and prioritizing work; team building and matching workers into teams; coordinating activity and providing communication across teams and motivation. They identify on average 20 occupations that consistently engage in organizational capital accumulation across OECD countries. Management occupations make up a core of these occupations, but are not the only contributors to organizational capital. They also identify professionals and associate professionals in science and engineering, health, education, and business administration as those workers who contribute to the accumulation of organizational capital. They find that managers account for less that 50% of total employment and investment in organizational capital. Indeed, in a separate study Corrado and Hulten (2010) find that managers spend around 80% of their time on day-to-day activities, most of which should not be counted towards organizational capital accumulation. When considering the definition of organizational capital, is important to remember that is related to, but distinct from managerial capital.

In this paper, I embed the two important components of most definitions of organizational capital into the model. First, I explicitly model organizational capital as input into firm production, hence emphasizing its importance for the firms. Secondly, I endow the firm with organizational capital, so if the firm exits, all of its organizational capital is lost. At the same time, I assume that only skilled workers can accumulate organizational capital, hence recognizing that some organizational capital is embedded in the firm's skilled employees.

1.2.2 Measuring Organizational Capital

Together with the lack of a precise definition, another difficulty associated with studying organizational capital is that it is inherently hard to measure. All of the definitions emphasize that organizational capital is some sort of knowledge that makes a firm operational and successful, but this type of knowledge is different across firms. A large stock of organizational capital will look different for different organizations, because the success of delivering a "want-satisfying good" looks different for different organizations. This, together with its tacit nature, makes a direct measure of organizational capital virtually impossible to develop. In its place, three main approaches are used instead.

Firstly, researches have looked for approximate ways to measure investment into organizational capital using available data. One of the most transparent proxies for measuring organizational capital investment is the firms' Selling, General and Administrative (SG&A) expenditure, first proposed by Lev and Radhakrishnan (2005). The argument is that even though SG$A expenditure covers more than expenditure on investing in organizational capital, such as expenditure on advertising, the majority of costs associated with creating new organizational capital will be covered in SG&A expenditure. Eisfeldt and Papanikolaou (2013) , discussed above, measure organizational capital as the cumulative sum of SG&A expenses using the perpetual inventory method. Carlin et al. (2012) also use this method, as well as some proxy measures for the density of social networks within an organization, which corresponds to their particular definition of organizational capital as firm-specific language. Lev et al. (2009) also use SG&A expenditure as a proxy for investment in organizational capital and examine the effect of organizational capital on firm performance by estimating the deviation of the company's actual revenue and costs from predicted revenue and costs based on the tangible resources available to the firm, such as capital and labor. They find a positive relationship between their measure of organizational capital and future performance, such as operating income growth, sales growth and abnormal returns, as well as higher executive compensation. Although transparent, this method of measuring OC investment is bound to overestimate it, as SG&A expenditure includes R&D, marketing and software expenditure.

Instead of using proxies available in the financial data, other studies relied on administering carefully curated business surveys aiming at the measurement and evaluation of organizational practices within different firms. For example, Carmona-Lavado et al. (2010) measure organizational capital using responses to whether the company has formal systems for project failures and success and formal discussions on learning from new products. Bloom and Van Reenen (2006) administer a survey of management practices across multiple countries to ascertain whether there is a difference in managerial practices across countries and to what extent they matter for firm performance. Using a survey to ascertain investment into organizational capital is costly and presents a problem of survey design that is very sensitive to the context and the particular question that the researcher looks to investigate.

The third method of measuring investment into organizational capital was proposed in Squicciarini and Le Mouel (2012) and relies on identifying tasks that are most likely related to organizational capital accumulation, calculating the frequency with which workers in different occupations perform those tasks and then estimating organizational capital investment by calculating the earnings and the employment of workers who often perform organizational capital related activities. Squicciarini and Le Mouel (2012) come up with a set of 19 occupations that they relate to the accumulation of organizational capital. These workers perform tasks such as planning activities, developing objectives and strategies, developing teams and training others. They find that many of the organizational capital related tasks are performed by workers in managerial occupations, however, other occupations, such as professional and associate professional in science, engineering, health, education and business administration are also important contributors to organizational capital accumulation. Using this methodology, they find that on average across 20 countries investment in organizational capital constitutes 2.2% of value added within firms.

In this paper, I use a methodology conceptually related to the task-based methodology of identifying organizational capital investment. Based on the work of Squicciarini and Le Mouel (2012) described above and on the insights from Bloom et al. (2013), who find that management quality is related to managers' and employees' educational levels, I assume that organizational capital can only be accumulated by skilled workers and embed this relationship into a general equilibrium model of firm dynamics. I then connect the novel empirical fact that the share of skilled workers in firms declines as firms age to the notion that younger firms will be making intensive investment in organizational capital and hence will need relatively more skilled workers, compared to their older counterparts. The idea that young firms in particular require organizational capital is not new. Hsu (2007) argues that entrepreneurs with previous experience with starting a business are rewarded by venture capitalists (VCs) when the entrepreneur is seeking financing for a new venture. He sees this as evidence towards the fact that the importance of organizational capital for the establishment in general and at the early stages of an its life is recognized by VCs. The argument is that for starting enterprises the founder will start off doing all of the work towards accumulating organizational capital, before they can hire outside help to do so, and the proven capability of the founder to accumulate organizational capital is seen as an advantage by VCs. I interpret the decline in the share of skilled workers in firms as they age as evidence that these firms start off investing intensely in organizational capital and then reduce their pace of organizational capital accumulation as they get closer to their optimal scale, and I use this decline as a key moment to discipline the model, which I present in the next section.

1.3 Model of Organizational Capital

In this section, I present a model of firm growth where growth is generated via two channels. Firstly, firms grow because they have an incentive to invest in organizational capital. Secondly, growth is generated via an exogenous increase in firm productivity. I introduce exogenous productivity growth in order to be able to abstract away from other sources of firm growth that are important, such as physical capital accumulation or customer capital accumulation, but that are outside the scope of this paper. This abstraction allows me to explore to what extent the accumulation of organizational capital alone can generate firm growth. The general model framework is based on the Hopenhayn (1992) seminal industry dynamics model, but differs from it in two important ways. Firstly, as mentioned above, in this model firm productivity grows at a deterministic exogenous rate without random shocks, as opposed to following at AR(1) process like in the original Hopenhayn (1992) work. Secondly, I embed organizational capital into the production process. I make two important assumptions about how organizational capital enhances firm production. I introduce organizational capital, Z, directly as a factor of production into the production function. In addition, I assume that organizational capital cannot directly be purchased in the market, but has to be accumulated within the firm by skilled labor. The assumption that only skilled labor can accumulate organizational capital relies on the work by Mouel and Squicciarini (2015) that finds that all the occupations that contribute to organizational capital accumulation are skilled occupations. I also assume that skilled labor enters the production function directly. Hence, the firm faces a trade-off between using skilled labor to invest in future organizational capital or using skilled labor for current production. This organizational capital accumulation setup formalizes the notion that organizational capital is at least partially embodied in the firm's employees, as described above. At the same time, firms can be hit by an exogenous exit shock, at which point all of the organizational capital that the firm has accumulated is lost, formalizing the notion that organizational capital is a firm property, rather than a worker property. I calibrate the model and use the calibrated version to quantify how much firms invest in organizational capital and how much of firm growth can be attributed to its accumulation.

1.3.1 Production Function

I introduce a new factor of production in the production function: organizational capital, Z. It is modeled as intangible capital that cannot be purchased in the market but can instead be accumulated by skilled labor specifically designated to this task. I consider a single industry, so subscript i indicates a firm specific value and subscript t for time is omitted for simplicity unless needed. The-firm specific production function takes the following form:

$$Y_i = \tilde{A}_i Z_i^{\alpha} {S_{p_i}}^{\mu} U_i^{1-\alpha-\mu} \tag{1.1}$$

where U_i represents unskilled labor and S_{p_i} represents skilled labor used in the production of the firm's good. For calibration simplicity, this production function does not include physical capital, however, including it is a simple extension. At each given period, firms are heterogeneous in their level of productivity, A, and the level of organizational capital that they have accumulated, Z. In order to accumulate organizational capital, the firm needs to dedicate some skilled workers to the task of investing into new organizational capital, so the firm decides how the skilled workers divide their time between working on production-related tasks and organizational capital related task. The decision to invest into organizational capital is made today and the value or organizational capital today is fully determined by the decisions made in the previous period. The law of motion for organizational capital is as follows:

$$Z_{t+1} = (1-\delta)Z_t + {S_{oit}}^{\theta} \tag{1.2}$$

with $0 < \theta < 1$, so the model assumes diminishing returns to investing into organizational capital. The assumption stems from the intuition that for any given level of organizational capital at some point adding more skilled labor to come up with a blue print, a standard for a production process or a business plan is no longer as productive as adding the first unit of skilled labor to this task. I assume that organizational capital depreciates at some non-zero rate $0 < \delta < 1$. This assumption formalizes the idea that even though at one point the firm may have developed a way of doing business and compiling physical and human capital in a way that is optimal for its current market conditions, a change in market conditions or customers' taste may render the previous optimal outcome obsolete and require additional investment into organizational capital.

1.3.2 Demand

As in this paper I am interested in firm growth, I do not explicitly model the household side of the economy. Demand for the firm's good is assumed to derive from the final good sector, which uses a CES aggregator across individual inputs:

$$Y = N^{\frac{1}{1-\rho}} (\sum_{i=1}^{N} Y_i^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}} \tag{1.3}$$

where $\rho > 1$ is the elasticity of substitution, N is the number of establishments in the industry and $N^{\frac{1}{1-\rho}}$ is the adjustment factor to make the degree of substitution scale-free[1]. Applying the first order conditions gives each establishment the following inverse demand curve with elasticity ρ where the industry price is normalized to be $P = 1$

$$P_i = (\frac{Y}{N})^{\frac{1}{\rho}} Y_i^{-\frac{1}{\rho}} = BY_i^{-\frac{1}{\rho}}$$

where B represents the demand shifter that will later be used for the numerical estimation of the model. The production and the demand functions give rise to the firm's revenue function:

$$P_i Y_i = A_i Z_i^a S_{p_i}^{\ b} U_i^c \tag{1.4}$$

where $A_i = \tilde{A}_i^{1-1/\rho}$, $a = \alpha(1-1/\rho)$, $b = \mu(1-1/\rho)$ and $c = (1-\alpha-\mu)(1-1/\rho)$ are defined for simplicity. Firms hire skilled labor for production and organizational capital investment at the spot market wage w_s and unskilled labor at the spot market wage w_u. The wages for skilled and unskilled workers are such that $w_{ut} = W_u(N_u)$, $w_{st} = W_s(N_s)$, where N_u and N_s are aggregate labor demand for unskilled and skilled labor respectively. Firms also pay a fixed operational cost C_f each period that they choose to remain open. This defines the following firm profit function:

[1]For an example of a derivation, see Alessandria and Choi (2007)

$$\Pi_i = A_i Z_i^a {S_{p_i}}^b U_i^c - w_s(S_{p_i} + S_{oi}) - w_u(U_i) - C_f$$

Given that the choices of skilled and unskilled labor in production are made contemporaneously given the spot market wages, the optimal choice of S_{pi} and U_i will be dictated by the first order conditions for the firm: $\frac{\partial PY(A,Z,S_p^*,U)}{\partial S_p} = w_s$ and $\frac{\partial PY(A,Z,S_p,U^*)}{\partial U} = w_u$. After imposing the skilled and unskilled labor optimality condition, I obtain the following revenue function for the establishment:

$$Y_i^*(A_i, Z_i) = A_i^* Z_i^{\frac{a}{1-c-b}}$$

where $A^* = (1-b-c)(\frac{w_u}{c})^{\frac{c}{b+c-1}}(\frac{w_s}{b})^{\frac{b}{b+c-1}} A_i^{\frac{1}{1-c-b}}$.

A_i follows an exogenous deterministic process where all firms start with the same productivity level, A_0, and once the firm enters, its productivity grows with an exogenous growth rate γ. The productivity evolution process is independent across firms and takes the following form for each firm:

$$A_{t+1} = \gamma A_t.$$

1.3.3 Incumbents and New Entrants

In this model, time is discrete and all agents face an infinite horizon. There are two types of agents: incumbent firms and potential new entrants. Each incumbent makes a choice whether to remain active or to exit. They also face an exogenous probability of exit, e. Exogenous exit is important as it helps match the fact that firm of all sizes exit in the data, something that a Hopenhayn (1992) type model struggles to match without an exogenous exit shock. Incumbents face the following problem (dropping the i subscript for clarity):

$$V(A_t, Z_t) = \max[V^c(A_t, Z_t), 0]$$

where the continuation value is defined as follows:

$$V^c(A_t, Z_t) = \max_{S_{ot}, Z_{t+1}} [A_t^* Z_t^{\frac{a}{1-c-b}} - w_s S_{ot} - C_f + \beta(1-e)V(A_{t+1}, Z_{t+1})]$$

$$\text{s.t.} \quad Z_{t+1} = (1-\delta)Z_t + S_{ot}^{\theta}$$

$$A_{t+1} = \gamma A_t$$

The incumbent can choose to exit before producing anything this period if the expected value of staying operational is below 0, or they choose to stay operational and choose optimal organizational capital for the next period by choosing how much skilled labor to hire for organizational capital investment this period. Given the evolution of firm-specific productivity and the fact that there are no negative productivity shocks, in this model, firms will only choose to exit at the beginning of their life cycle if they draw a low value of initial organizational capital.

There is free entry and a continuum of potential entrants that can enter with starting productivity A_0, which is known and the same across all firms, and level of organizational capital Z_0 from a known joint distribution $G(Z_0)$. The idea behind this assumption is that entrepreneurs who start firms will differ in their experience with running a firm, so I model this as an initial distribution of organizational capital. I endow all firms with the same A_0 as a simplifying assumption which aims to load all firm heterogeneity onto the difference in initial organizational capital. Subsequent deterministic growth of A is meant to approximate the sources of growth that are missing from the model but are definitely present in the data, such as physical capital accumulation or demand accumulation. Entrants do not observe the realization of Z_0 before entering and have to pay a one-time entry cost C_e. In equilibrium, the zero profit condition holds, so new establishments will enter until the expected value of entry is equal to the cost of starting a business. Hence, in equilibrium there will be a mass of new entrants M_e such that entry occurs until

$$C_e = \int V(A_0, Z_0) dG(Z_0) \tag{1.5}$$

The distribution of Z_0 is assumed to be drawn from a uniform distribution.

1.3.4 Recursive Equilibrium

The incumbent and entrant's problems outlined above generate a joint distribution of A and Z for all firms that are active in the economy at any given period, with $F(A,Z)$ being the cumulative joint distribution of all "active" A and Z in the economy. The law of motion for the firm distribution in the economy can be described as follows:

$$F_{t+1}(A_{t+1}, Z_{t+1}) = \int \int_I dF_t(A_t, Z_t) + M_e \int^{Z_{t+1}} g_t(Z_0) dZ_0 \tag{1.6}$$

where

$$I = \{(A_t, Z_t) \quad \text{s.t.} \quad V^c(A_t, Z_t) \geq 0, \quad Z_t(1-\delta) + S_{ot}^{\theta}(A_t, Z_t) \leq Z_{t+1}, \quad A_{t+1} = \gamma A_t\}$$

The recursive equilibrium can then be defined as follows. Let the distribution of operating establishments over the two dimensions of heterogeneity be denoted by $F_t(A,Z)$ and let Θ_t denote the vector of aggregate state variables. For a given Θ_0, a recursive equilibrium consists of:

1. Value function $V(A,Z)$,

2. policy functions $Z'(A,Z)$ and $S_o(A,Z)$,

3. prices w_s and w_u and

4. distribution of operating establishments $F(A,Z)$

such that given the prices w_u and w_s

1. $V(A,Z)$, $Z'(A,Z)$ and $S_o(A,Z)$ solve the incumbents' and the entrants' problem

2. Markets clear

For the numerical solution of the model, I will focus on a stationary recursive equilibrium where $F_{t+1}(A,Z) = F_t(A,Z)$. As shown in Hopenhayn (1992), in a stationary equilibrium prices remain constant and known to all the firms, so in the estimation I assume that w_u and w_s do not change across time.

1.3.5 Numerical Estimation and Calibration

The algorithm used in the numerical estimation is closely based on Bloom et al. (2016). First, I solve for the value function of the incumbent firm that makes the decision to either continue operation or exit and takes demand as given. After acquiring policy functions Z and S_o from the value function iteration and S_p and U from the static first order conditions, I then iterate over the demand curve to satisfy the zero-profit condition. The demand shifter B adjusts until the entry cost is equal to the expected value of entry. If the expected value of entry is above the entry costs, then more establishments enter and B falls, decreasing the value of entry and pushing the model towards the equilibrium. A time period in the model is a year in order to keep consistent with the data described below. I then simulate data for 26,000 firms over 100 years to get to a steady state firm distribution, and then keep the last 20 periods of the simulated data to match the time span of the panel data and acquire moments used in the parameter estimation.

In order to numerically solve the model, I need to define a set of 13 parameters, 12 for the model and 1 for the grid definition in the numerical estimation. I list the four parameters that I predefine from existing literature in Table 1.1. I pick the demand elasticity $\rho = 5$ from Bartelsman et al. (2013), which is a standard estimate in the literature. I normalize the wage of unskilled workers to be 1. I use the measure of the skill premium from the data defined as the ratio of the average wage for college graduates to the average wage for workers without a college degree to pin down w_s. I also set the entry cost C_f such that the ratio of the entry cost to the operational fixed cost is $\frac{C_e}{C_f} = 0.82$, following estimates in Barseghyan and DiCecio (2011).

I rely on previous literature for the estimates of two important parameters related to organizational capital. Firstly, I rely on Mouel and Squicciarini (2015) for the estimate of the depreciation rate for organizational capital. Mouel and Squicciarini (2015) use the retention rate of workers linked to organizational capital investment to estimate the depreciation rate of organizational capital, which they find to be 10%. I also set α, the elasticity of output with regards to organizational capital, to 0.1 following Bloom et al. (2016). In their paper, they incorporate managerial capital into the firm production function and estimate managerial capital - output elasticity using experimental evidence from Bloom et al. (2013). In Bloom et al. (2013), they run an experiment in which they hire management consultants for a set of textile firms in India, with a randomized intensity of treatment, and measure to what extent this intervention leads to the improvement in firm performance. Even though management capital and organizational capital measure different types of intangible capital, management consulting - the basis of the intervention in the Bloom et al. (2013) experiment - has been closely linked to accumulation of organizational capital. Indeed, Corrado et al. (2009b) measure aggregate organizational capital as 80% of the revenue of the management consulting industry. Hence, I borrow Bloom et al. (2016) estimate for the elasticity of output with respect to management capital and use it as a measure of the elasticity of output with respect to organizational capital.

Table 1.1: Calibrated Parameters From the Literature

Parameter	**Symbol**	**Value**	**Source**
Demand Elasticity	ρ	5	Bartelsman et al (2013)
Discount Factor	β	$1/1.1$	10% interest rate
Organizational Capital - Output Elasticity	α	0.1	Bloom et al. (2016)
Depreciation of Organizational Capital	δ	0.1	Mouel and Squicciarini (2015)

The remaining parameters are set by matching important moments in the data to the corresponding moments in the simulated panel. I use the average exit rate and the survival rate until the age of 5 to inform the cost of entry C_e and the probability of exit. I pin down the initial value of productivity, A_0, using the relative size of entrants to the average size of all active firms, and the growth rate of A, γ, using the average year-to-year growth rate measured as the difference of log of size. The two remaining parameters are specific to the setting of my model. To my knowledge, there is no other structural model that quantifies the importance of organizational capital for firm growth or how organizational capital evolves throughout the life cycle of the firm. Given the non-standard factors of production I use in my production function, I cannot rely on NIPA factor shares to inform me of the values of the exponents in the Cobb-Douglas production function. I use the share of the firm wage bill spent on skilled labor in the total wage bill of the firm, where skill is defined as workers with a college degree, to inform the value of μ, the exponent on the skilled labor in the production function. I use the average change in the share of skilled workers in a firm across the first 2 years of its life in order to discipline θ, the elasticity of investment into organizational capital with respect to skill labor. Finally, in order to set the scale for the grid of organizational capital in the numerical estimation of the model, I estimate a "base organizational capital" parameter that I use to discipline the grid using the share of skilled labor in entrant firms. The next section presents the empirical results that I use in order to pin this parameter down.

1.4 Worker Skill Composition

In this section I present the novel empirical results that I use for calibrating the model outlined above. I examine how the composition of skill in the firm evolves as firms grow bigger in size and as they grow older, as well as the cross-sectional distributions of skill across firms.

1.4.1 Data

I use the *Relação Anual de Informações Sociais* (RAIS) dataset, which is a yearly administrative employee-employer matched panel dataset from Brazil for both private and public workers in the formal sector spanning years 1987 to 2014. It is considered to be a high-quality census of formal workers in Brazil (Dix-Carneiro (2014)). The main unit of observation is a worker, each with a unique ID number constant across time, and the dataset contains a wide range of demographic characteristics, such as age, race, sex and years of schooling, as well as detailed occupation information and tenure at the firm measured in months. The compensation data is reported in reals per month, and includes salary as well as other benefits. Starting in 1994 I also observe the contractual number of hours worked per week, which allows me to construct real hourly wages for workers. I use real hourly wages to construct one of the measures of firm's average skill level, so I restrict my attention to firms born in or after 1994. This leaves me with a 20 year span, from 1994 to 2014. The dataset also contains firm and establishment unique tax identifiers, which allow me to follow firms across time, as well as the 5-digit industry in which they operate and the municipality in which they are located. For the empirical results presented below, I exclude "firms" in the public sector, as well as firms in the education and health care industries.

A potential problem with using the RAIS dataset to study firm dynamics is the fact that it only collects data on formal workers in formal firms, which presents a potential problem with the presence of informal firms and establishments. As noted in Ulyssea (2018), around 30% of workers in Brazil are employed in informal firms[2]. To an extent that the choice to formalize is not random and can be correlated with the wage setting policy and personnel choice in the firm, the exclusion of informal enterprises presents a source of bias when estimating how firms change the composition of the workforce as they expand and grow older and how the composition of skill in firms varies in the cross-section. However, it is also the case that informal firms tend

[2]To my knowledge, no convenient statistic on the proportion of informal enterprises in Brazil is available.

to be small in Brazil [3]. For that reason, in the main analysis presented further, I consider firms with at least 3 workers on average throughout their life cycle, to reduce the bias associated with looking at formal firms only. [4] This restriction leaves me with around 76% of the sample, and my final dataset consists of 211,431 unique firms and 1,412,645 firm-year observations.

The second concern associated with RAIS including only formal workers and firms has to do with the potential presence of informal workers in formal firms and establishments. Ulyssea (2018) finds that indeed a large share of formal firms and establishments in Brazil do employ some informal workers. To the extent that the tendency to register informal workers is correlated with establishment size, the results presented further might bear a different interpretation than the one that I propose. It is possible that what I classify as firms expanding in the data is actually firms formalizing their previously informal workers for reasons that have nothing to do with positive demand or technology shocks that would propel them to expand, and not making a change in their actual worker composition. As I do not have information on the informal workers, I cannot fully safeguard again this source of bias.

As I am interested in the change in the composition of the workforce in the firm, I keep all of the workers in the establishment, without regard for gender, age or full-time / part-time status. As a measure of size, I use total employment at the firm, as RAIS does not carry any financial information about the firm. I adjust the total employee count by the number of months that the worker was employed in the firm in the year, so a person employed for 6 months counts as 0.5 employee-years in the measure of total yearly employment in the firm, as well as in the measure of skilled employment.

RAIS contains information on both the establishment and the firm that the worker is employed at. In the main body of the paper, I will focus on firm-level results, because arguably the choice of personnel and the choice of investment in organizational capital is made at the firm,

[3] Ulyssea (2018) documents that the probability of a firm being informal decreases sharply with size, with fear of greater visibility for tax-collecting authorities being the possible reason

[4] The results carry through with other size cutoffs as well, as presented in the Appendix

rather than establishment level. 90% of the firms in my sample are 1-establishment firms, and 60% of establishments belong to 1-establishment firms. All of the results presented below carry through when using establishment, rather than firm-level data, as shown in the Appendix.

1.4.2 Measure of Skill

In this paper, I use two measures of skill. The main measure of the skill composition in the firm is the share of workers with a college education. I divide the sample of workers into two education categories:

- $Coll+$, which includes people with a college degree or above;
- Everyone else.

By construction, at any given period each worker can belong only to one of the two groups. I use educational attainment as a proxy for the skill level of workers, with the assumption that educational attainment conveys some information about the skill of the worker as perceived by the firm when they hire them. Using educational attainment as a measure of average skill in the firm has a number of important advantages. First of all, it presents a clear-cut distinction between the two skill categories that is marked with an official diploma and is presumably easily interpretable to both the firm and the researcher. It also has a direct relationship with the model that uses a binary definition of skill and translates into the assumption that only college educated workers can invest in organizational capital.

On the other hand, it is possible that in a context such as Brazil, where education attainment is in general low, especially with regards to college education, it is a poor signal of skill, and there are other characteristics, unobserved to the researcher, that inform potential employees about the skill of a given worker and influence their decision to hire them. Indeed, college educated workers make up a small share of the total sample, only 8%, and there are alternative ways of dividing workers into skill categories in the workforce. Mueller et al. (2017) use a skill

Table 1.2: Summary Statistics: Education Categories

	Prim		HS		Coll	
	Mean	SD	Mean	SD	Mean	SD
Log of Wage	0.17	0.52	0.48	0.58	1.57	0.89
Hours (weekly)	43	4.2	42	4.2	40	4.4
Share of Sample	0.51		0.41		0.08	
N	15,794,605		12,725,910		2,257,214	

classification employed and designed within the firm itself, where workers are explicitly divided into skill groups, mostly based on the type of occupations that they have. Others have divided occupations into managerial and non-managerial or cognitive and routine (Autor et al., 2003). These are all valid alternatives to my approach that I do not explore in this paper.

Nonetheless, Table 1.2 and Table A.1 provide some evidence that the classification based on the level of education does convey some information about what the workers end up doing in the firm and how the firm perceives their skill level. Table 1.2 displays summary statistics for wages and weekly working hours for workers divided into three education groups: workers only with a primary school education, workers with a high school diploma and workers with a college degree. The most important thing to note is that there is a clear increasing relationship between the level of educational attainment and the wage. If we assume that firms reward skill with higher wages, then Table 1.2 suggests that my chosen education category does convey some information about the skill level of the workers, as I assume that workers with higher educational attainment are more skilled. Table A.1 in the Appendix shows the 10 most frequent occupations across the three educational categories outlined above. Even though there is some overlap across the groups, the workers in the college educated group have mostly different jobs than the workers in the high school and in the primary school category. The workers in the *Coll* category are mostly employed in occupations that imply a more managerial and a higher-skilled role. It is also important to note that the occupations of the college educated workers presented in Table A.1 are closely related to the occupations that Squicciarini and Le Mouel (2012) identify as the occupations that contribute to the investment of organizational capital, hence further justifying the use of education as the skill group that is involved in the accumulation of organizational capital in the model. I will use college education as the main definition of skill in the model.

Alternative Measure of Skill

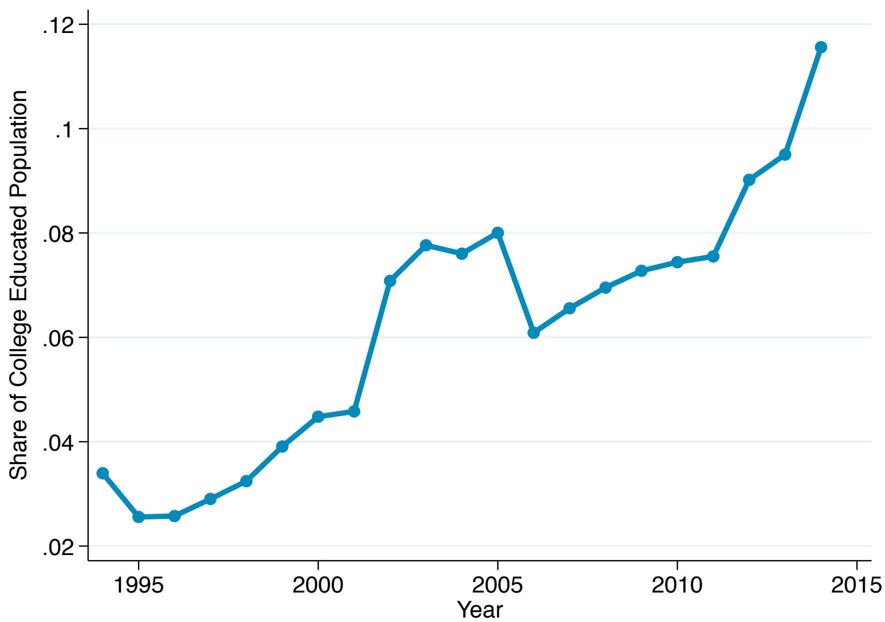


Figure 1.1: The change in the share of college educated workers in the sample.
Notes: the share is calculated as the share of the total workforce in the sample in a given year.

Throughout the sample time frame, Brazil has undergone a huge increase in educational attainment. The total share of workers with a college degree in my sample has steadily increased from 1994 to 2014, as can be seen in Figure 1.1. This makes the exploration of how skill composition in the firm changes with age more complicated: as firms get older they might mechanically have more skilled labor, as there is more skilled labor available in the worker pool in the later years. I use an alternative measure of skill in order to check how the share of skilled workers changes as the firm ages which is inspired by the methodology of Card et al. (2013) and Hagedorn et al. (2017) and uses the worker fixed effect from the following regression as a measure of skill:

$$\text{LogWage}_{wt} = i.\text{year} + \text{age}^2 + \text{age}^3 + \alpha_w + \varepsilon_{pt} \tag{1.7}$$

I construct a dataset with the full working history of all the workers who have ever been employed by the firms in my sample. Then the worker fixed effect in the regression captures the component of the worker's earnings that is attributed to workers time invariant characteristics and their education, as I do not include educational attainment in the set of controls. I choose to do so because there are skills acquired via formal education that might be important for the accumulation of organizational capital. As a robustness check, I perform the analysis described below with education included in the regression and arrive to similar results, as shown in Appendix A. Once I have a measure of individual skill, I then average this measure across all workers in the firm in a given year to arrive to a firm-level measure of skill composition. This measure employs a less restrictive definition of skill, but does not have a direct theoretical counterpart in the model, as the model has two discreet skill types of workers and this measure describes a continuum of skill levels in the population. I replicate the empirical analysis with this measure of skill as a robustness check.

1.4.3 Sample Selection

For the main empirical analysis that I use to calibrate the model, I use a subsample of the firms in the data, namely the firms that employ at least one college educated (Coll) worker for at least a month in the year when they are born. This restriction leaves me with 21% of the firms that employ around 50% of the workforce in my full sample. This sample is not a representative sample of Brazilian firms. The firms in my restricted sample are different in many ways from the firms that start off without any college workers. The two panels of Figure 1.2 and show that these firms pay higher wages and are bigger at every point in the distribution. I include this

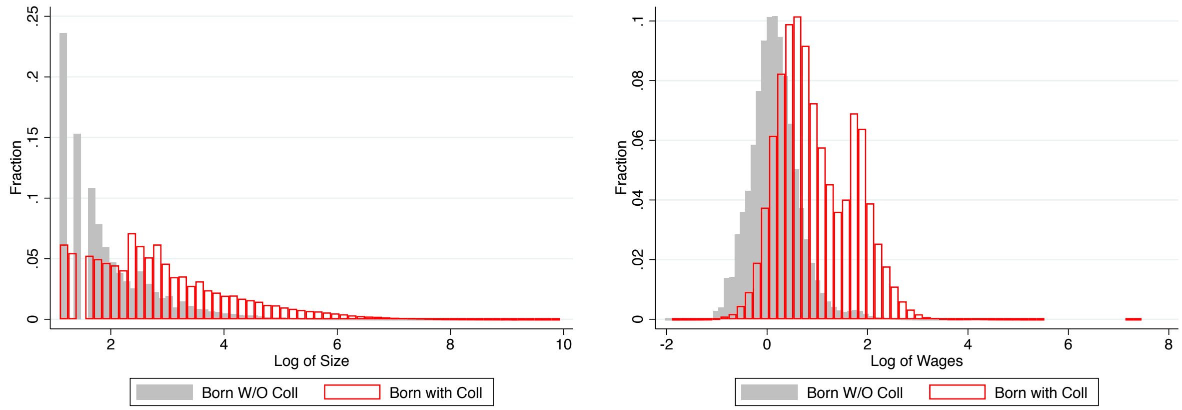


Figure 1.2: All firms vs. "Well-performing" firms

Left: Distribution of log of firm size measured as number of workers in firms that hire college educated workers when they enter versus firms that do not hire any college educated workers when they enter. Right: Distribution of log of wages in the two samples of firms.

restriction for two reasons. Firstly, this restriction allows me to focus on well-performing firms that pay higher wages and end up growing bigger, firms that are likely to have accumulated a lot of organizational capital that allowed them to develop and maintain a competitive advantage. Secondly, the firms in the model presented in this paper need both skilled and unskilled labor to produce at any age. Given that I use educational attainment as the main measure of skill, I want to calibrate the model to the firms that have college educated workers at birth. Hence, this sample restriction represents the firms that are closest to the firms described in the model.

Table 1.3 presents the summary statistics of the sample that I use for the empirical analysis. On average, firms survive for just under 6 years. The average share of college workers is around 33% at birth and 23% considering all firms at all ages. The final sample restriction leaves me with around 50,000 unique firms and 150,000 firm year observations.

1.5 Worker Skill Composition and Firm Life Cycle

This section presents the empirical results that pertain to how skill composition varies within firms as they grow bigger and older and across firms in the cross-section. It discusses

Table 1.3: Summary Statistics: Firm Level

	Mean	SD
Log of Size	2.45	1.4
Age of Exit	6.62	4.45
Average Share of Coll Workers	.23	.26
Average Share of Coll Workers at Birth	.33	.29
N	154,056	

the results for the restricted sample using the share of college educated workers and the average worker fixed effect. The results for the full sample are presented in the Appendix.

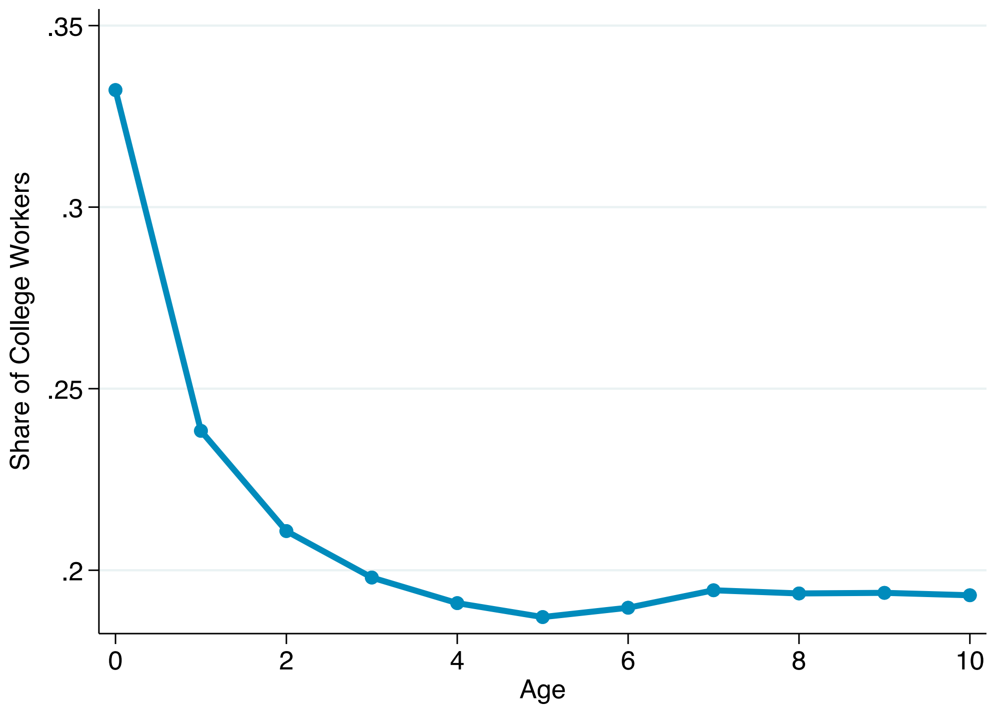


Figure 1.3: Firm Skill and Firm Age: Cross-Section

The main empirical insight of the paper is summarized in Figure 1.3, and it also demonstrates the numerical relationship that I will be using in the model calibration. Figure 1.3 plots the relationship between the share of college educated workers in the firm and firm age, where each dot is the average share of college educated workers in a firm of a given age averaged across all years. There is a clear change in the skill composition of firms across different ages: entrant have a relatively high proportion of skilled workers and older firms seem to have substituted away from skilled labor towards unskilled labor. In fact, over the first 2 years of their lives, firms on average decrease the share college educated workers that they employ by 9% - a moment that I use in the calibration of the model. I argue that this relationship is driven by the fact that firms have a strong need to accumulate organizational capital when they enter the market, for which they need a lot of skilled labor. As firms age, they get closer to their optimal levels of organizational capital, which leads to them hiring mostly unskilled workers that participate in the production process that has been outlined and codified by the skilled workers at the early stages of the firm's life-cycle. Figure 1.3 represents a simple average across firm age without additional controls, so in the following section I confirm this negative correlation between the share of college workers and age using regression analysis in the cross-section of firms and across firms' life cycle.

1.5.1 Firm Skill Composition and Firm Size and Age

For the main analysis in the paper, I employ two regression specifications. I use firm-level regressions to look at how average skill in the firm varies with size and age in the cross-section and in the life-cycle. The *cross-section* regression has the following specification:

$$\text{AveSkill}_{it} = c + \beta \text{LogN}_{it} + \alpha_{age} + \alpha_t + \alpha_r + \alpha_{ind} + \varepsilon_{it} \tag{1.8}$$

where α_{age} represents age fixed effects in years, α_t represents year fixed effects, α_r represents region fixed effects[5] and α_{ind} is 5-digit industry fixed effects. The standard errors are clustered at the industry level.

[5] Where region is a 2-digit municipality code

The *life cycle* regression has the following specification:

$$\text{AveSkill}_{it} = c + \beta \text{LogN}_{it} + \alpha_t + \alpha_{age} + \alpha_i + \varepsilon_{it} \tag{1.9}$$

It is very similar to the cross-section regression specification but differs in that it includes firm-level, rather than industry-level fixed effects. The cross-section specification examines how the average skill in the firm varies with size and age in the cross-section of firms in the same region and narrowly defined industry in the same year. The life cycle specification examines how average skill in the firm changes with size and age within the same firm. firm-level fixed effects absorb all the variation stemming from time-invariant characteristics of the firm, so it uses the within-firm changes in size and age as a source of identifying variation. The coefficients of interest in both regressions are β and the coefficients on the age fixed effects. Both regressions present correlation results only.

1.5.2 Results: Share of College Educated workers as Average Skill

To start, consider the share of college educated workers as a measure of average skill in the firm. The results that examine how average skill in the firm changes with size are presented in Table 1.4, where the coefficient of interest β is presented for both the cross-section and the life cycle regressions. We see that for this particular sample, where the firms are born with some college educated workers, there is a negative correlation between the share of college workers in the firm and firm size for both regression specifications. The life cycle result is of particular interest. It indicates that when looking at the same firm throughout its life cycle, controlling for age, the firm will on average have a relatively less skilled workforce when it grows larger. To my knowledge, this is a novel fact that might help shed light on how firms grow and how their needs for skilled labor evolve across time. Whether this is done by only adding low-skilled workers or by also replacing some high-skill workers with low-skilled workers is an interesting question

Table 1.4: Average skill measured as Share of Coll Workers in a Firm and Size

	(1) Industry FE	(2) Firm FE
Log of Size	-0.042***	-0.057***
	(0.004)	(0.007)
Constant	0.426***	0.539***
	(0.062)	(0.044)
Observations	154,005	154,005
R-squared	0.284	0.712
Year FE	Yes	Yes
Region FE	Yes	No
Industry FE	Yes	No
Firm FE	No	Yes

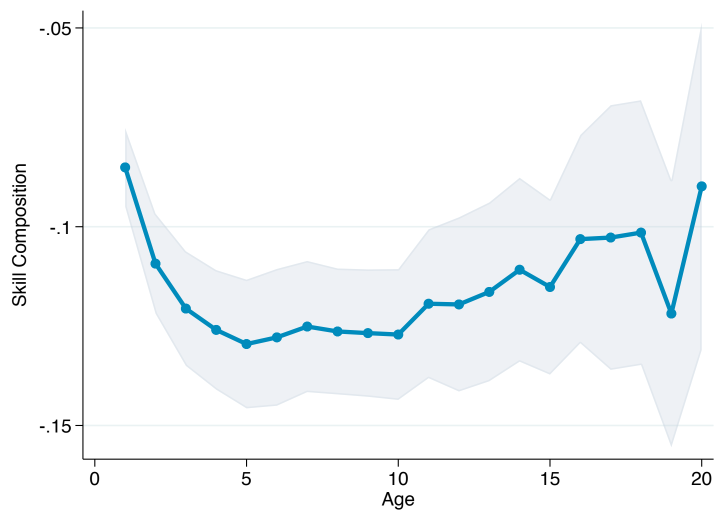
Notes: includes firm age FE. Standard Errors clustered at the industry level. Average skill measured as the share of workers with a college degree in the firm.
$*p < .10, **p < .05, ***p < .01$.

that I explore in Chapter 2 of this dissertation.

Now consider Figure 1.4 that shows how the average level of skill in the firm changes with age in an unbalanced panel of firms and in a balanced panel for multiple survival ages. It plots the coefficients of the age fixed effects from regression 1.8, the cross-section specification, along with 95% confidence intervals, where age 0 is the omitted category. Each coefficient represents the difference between the share of college educated workers in the firms of a given age and firms that have just started operating. Panel A presents the results for all firms in an unbalanced panel. It is clear that older firms in the same year, region and industry, controlling for firm size, have on average a less skilled workforce than their younger counterparts. The relationship is steadily decreasing in age for younger firms, until is tapers off somewhat around the age of 5. The fact that older firms on average have a less skilled workforce in the cross-section is a novel fact. The regression results presented in Panel A do not account for the fact that there is potential selection based on how long the firm survives. Firms that contribute to identifying the coefficient on older age are firms that survive to this age, and they might have some unobserved characteristics that also might induce them to hire fewer college educated workers. In order to counteract this, I run regression 1.8 on subsamples of firms separated by age of exit. The results are presented in Panel B of Figure 1.4 for survival ages 2 to 10, and also for survival age 15 for simplicity of exposition. We can see that the same pattern persists and that firms that survive for longer do not behave differently compared to firms that exit after only a few years of operation. On average, older firms have a less skilled workforce for all firms regardless of how old they are when they exit.

The patterns are similar when looking at what happens to the share of college educated workers as firms age, following the firms through their life cycle rather than comparing firms in the cross-section. The results are presented in Figure 1.5 Panel A for the unbalanced panel and Panel B for a balanced panel of firms for several survival ages. We can see that as firms age, controlling for size, the share of college educated workers decreases. The unbalanced results presented in Panel A of Figure 1.5 depict a U-shaped pattern where there is a decrease in average skill in the firm at the beginning of its life that then reverses around the 5-year mark, but never quite gets to the initial level of the share of college educated workers that the firm entered with. However, looking at Panel B of Figure 1.5, we can see that this is largely due to selection, as the results for balanced panel present similar results to what we saw for the cross-sectional analysis. When firms age, their workforce becomes less skilled on average, with the biggest decrease in the share of college educated workers happening in the first years of the firms' life cycle and the average level of skill stabilizing after the firm reaches the age of 5. There also seems to be no difference in how firms that survive until different ages change the average skill of their workforce as they age. The difference in the average skill-age pattern in the life cycle between the unbalanced and the balanced panel point towards a pattern of selection as to which firms end up surviving until older age. The fact that we do not see the same decreasing patter in the two

A



B

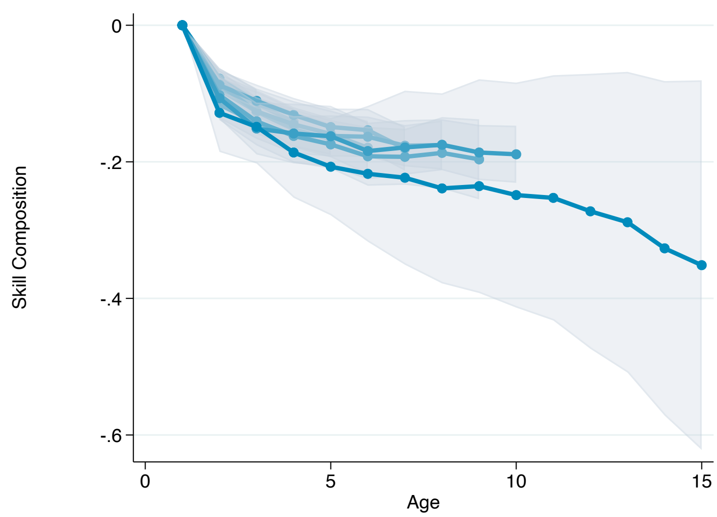
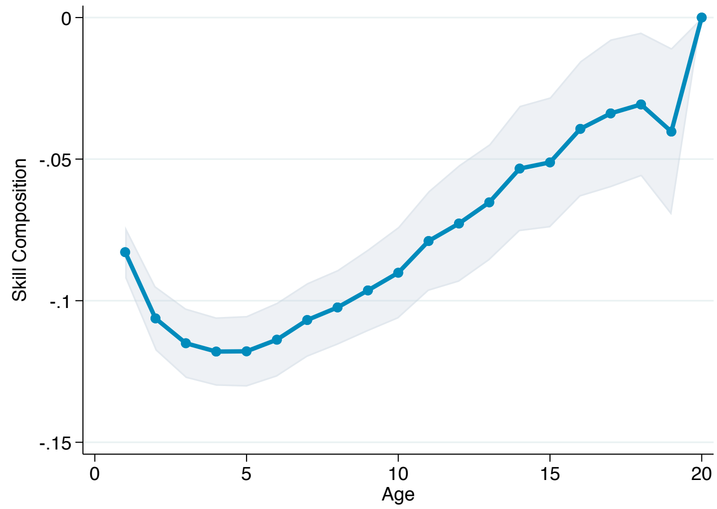


Figure 1.4: Firm Skill as Coll Share and Age in the Cross-Section: Unbalanced Panel and a Balanced Panel by Firm Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. Panel A shows the result of the regression in an unbalanced panel of firms. Panel B shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

A



B

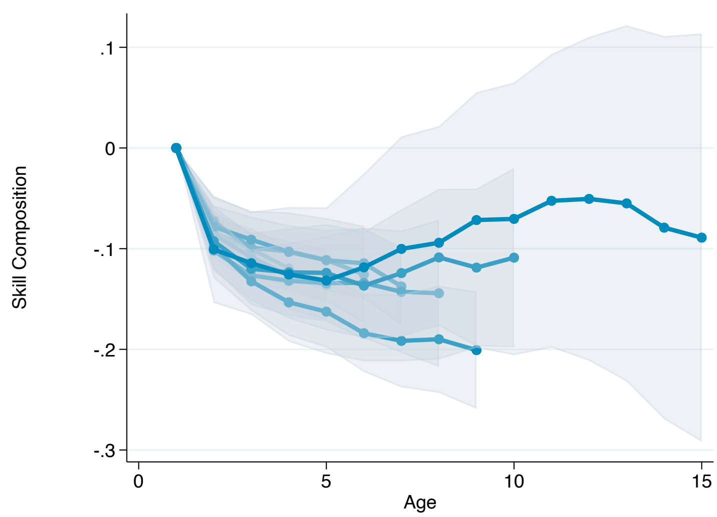


Figure 1.5: Firm Skill as Coll Share and Age in the Life Cycle: Unbalanced Panel and a Balanced Panel by Firm Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. Panel A shows the result of the regression in an unbalanced panel of firms. Panel B shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

panels of Figure 1.5 seems to indicate that firms that survive longer have on average a higher share of college educated workers in their workforce. I further explore the relationship between the average skill of the firm's workforce and its performance in Chapter 2 of this dissertation.

The overall results in this section suggest that older and bigger firms have a less skilled workforce, both when we compare firms in the cross-section and as we follow firms throughout their life cycle. Through the lens of the model outlined above, the evolution of skill in the firm as it grows in size and age is motivated by the firm's need to accumulate organizational capital. Bigger firms are closer to their optimal level of organizational capital, so they will be investing less in it as they approach their optimal scale and hence hire proportionately less skilled labor. Older firms will have been investing in organizational capital for a while and would be closer to their steady state level of capital, so would again have proportionately less skilled labor as they are no longer growing their organizational capital nearly as much as they were when they were young. The next section replicates the results discussed above using average worker fixed effects as a measure of firm skill composition, in order to confirm that the empirical patterns are not just applicable to the share of college educated workers as a measure of average firm skill and do in fact represent a broader pattern of firm behavior.

Results for the Alternative Measure of Skill

This section examines whether the results outlined above hold for the alternative definition of firm skill composition, a firm-year average of worker-level fixed effects from regression A.7.

Consider Table 1.5 which presents the results of the cross-section and life cycle regression specifications with the new definition of skill. It shows a somewhat different pattern than the results using the share of college educated workers as a measure of skill. In Column 1 we see that in the cross-section there is no significant correlation between average skill of the firm's workforce and firm size. However, Column 2 shows that the the same negative relationship be-

Table 1.5: Average skill measured as Worker Fixed Effect in a Firm and Size

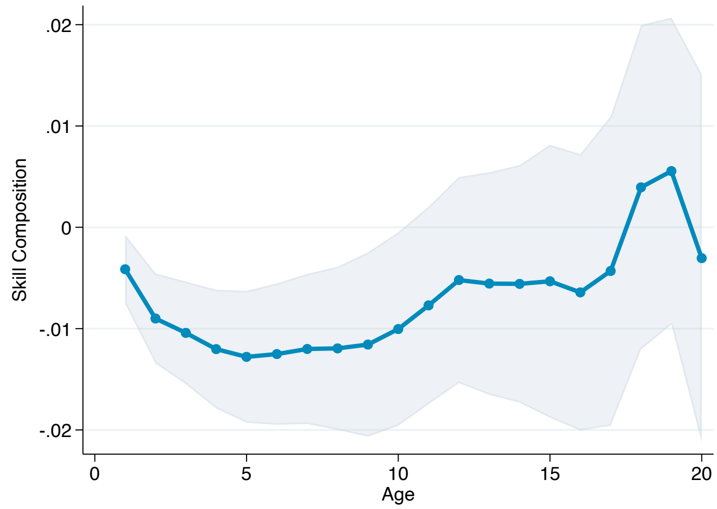
	(1) Industry FE	(2) Firm FE
Log of Size	0.000	-0.083***
	(0.010)	(0.009)
Constant	1.067**	1.017***
	(0.421)	(0.101)
Observations	149,845	149,845
R-squared	0.178	0.815
Year FE	Yes	Yes
Region FE	Yes	No
Industry FE	Yes	No
Est FE	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level. Average skill measured as the firm-level average of worker fixed effects from regression 1.7.
$*p < .10, **p < .05, ***p < .01$.

tween firm size and firm average skill if we look at the life cycle of the firm and examine how the average skill in the firm changes as the firm grows, which is in line with the results that use the attainment of a College degree as a measure of skill.

Figures A.4 and A.5 show how the average skill in the firm changes with firm age in the cross-section and in the life cycle when we use the alternative definition of skill. Figure A.4 presents the cross-sectional results (from the regression with industry, rather than firm fixed effects). It plots the coefficients of age fixed effects in regression 1.8 together with 95-% confidence intervals. Panel A of Figure A.4 shows an insignificant relationship between firm age and average skill in the cross-section for all firms, whereas Panel B shows the results of running regression 1.8 for a cross-section of firms that only survive until a given age. Both panels indicate that there is no significant relationship between age and average skill of the firm's workforce measured as average Mincer regression residuals, which differs from the results obtained using

A



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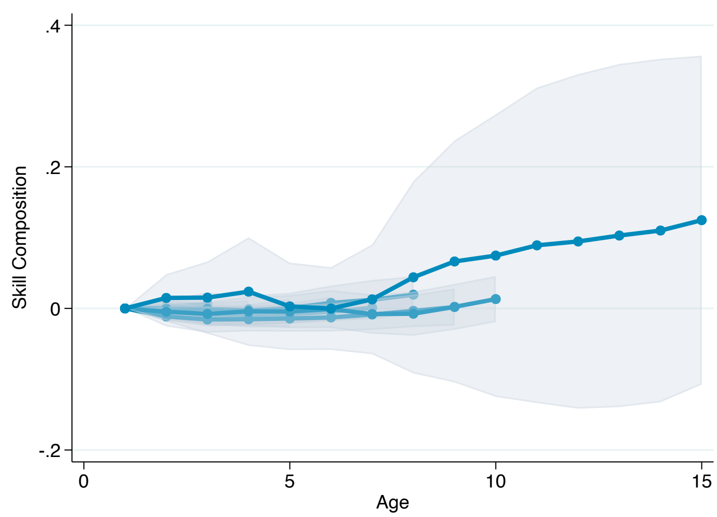
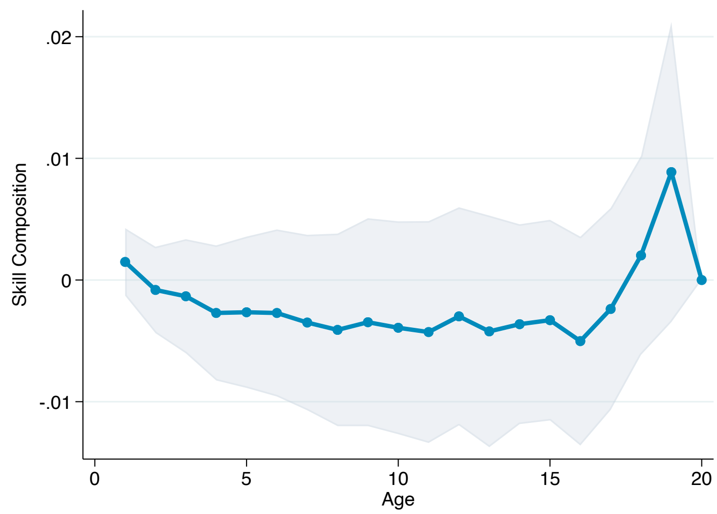


Figure 1.6: Firm Skill as Worker FE and Age in the Cross-Section: Unbalanced Panel and Firms by Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

the share of college educated workers as a measure of firm skill.

A



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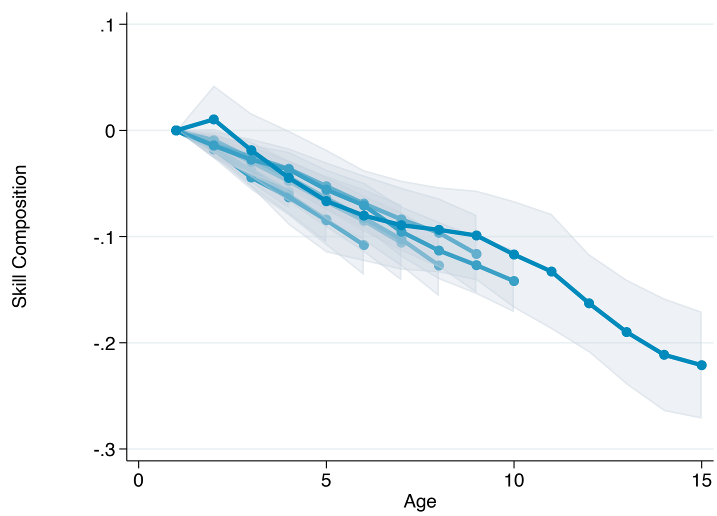


Figure 1.7: Firm Skill as Worker FE and Age in the Life Cycle: Unbalanced Panel and Firms by Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

The results of the life cycle regression presented in Figure A.5, however, support the conclusions of the previous section. Both Panel A, which shows the results of regression 1.9 in an unbalanced panel, and Panel B, which shows the results of regression 1.9 in a balanced panel of firm grouped by their exit age, show a negative relationship between the average level of skill and firm age, just as with the other measure of skill. The difference between the cross-section and the life cycle results when using Mincer residuals suggest that when looking at an arguably more sophisticated definition of skill, there is a stronger selection of which firms end up surviving the longest in the data based on how skilled the firm's workforce is. The results suggest that firms with a more skilled workforce tend to survive longer. The fact that the life cycle results agree across the two specifications with different definitions of average firm skill indicate that the results described above do not depend on the measure of skill used and describe a general pattern of how firms adjust the skill composition of their workforce as they grow older.

1.6 The Role of Organizational Capital in Firm Growth

1.6.1 Model Fit

Table 1.6: Parameters Calibrated in the Data

Parameter	**Symbol**	**Value**	**Method**
Growth Rate of A	γ	1.05	SMM
Starting Value of A	A_0	1.141	SMM
Skilled Labor - Output elasticity	μ	0.064	SMM
Skilled Labor - Org Capital elasticity	θ	0.10	SMM
Entry Cost	c_e	8.0	SMM
Exogenous Exit Rate	e	0.175	SMM
Reference Value for Organizational Capital Grid	Z_{Base}	0.62	SMM
Unskilled Worker Wage	w_u	1	Normalization
Skilled Worker Wage	w_S	1.79	Matching Skill Premium after normalizing w_u to 1

I use the negative relationship between the share of skilled labor in the firm and firm age to discipline a crucial parameter in the model - the elasticity of new organizational capital created with respect to the skilled labor dedicated to the task. The parameter values obtained via the simulated method of moments are outlined in Table 1.6 and the target moments and their model and data counterparts are outlined in Table 1.7.

The model moments match the data moments well, with only the relative size of entrants being noticeably higher in the model than in the data. The average annual growth rate of firms in the data and in the model is 21%, which is a high value that is consistent with the fact that the firms that start with college workers in Brazil are high-performing firms. The exogenous growth rate of productivity A in the model is 5%, corresponding to the value of γ of 1.05. The skilled labor-output elasticity μ is low, estimated at 0.064. In order to match the sharp decline in the share of college educated workers in the firm and the low overall share of college educated firms in the data, the share of skilled labor in the production function has to be low, as this share does not decrease with firm scale, like the share of workers who invest in organizational capital does.

The parameter of most interest is θ, the elasticity of investment into organization capital with respect to skilled labor, which is estimated to be 0.1. To my knowledge, this is the first estimate of this parameter in the literature. It controls how productive skilled labor is at investing in organizational capital, and the low value of the parameter indicates that there might be strong diminishing returns in the organizational capital accumulation process. As, to my knowledge, this is the first paper that sets out to explicitly model the link between skilled labor and organizational capital, there are no estimates in the literature that I can directly compare the value of θ to. The closest comparison can be made with the results in Corrado et al. (2009a) and Bloom et al. (2016). Corrado et al. (2009a) estimate that managers spend 80% of their time on managing and overseeing day-to-day activities and only 20% of their time on activities related to the future of the firm. Bloom et al. (2016) estimate adjustment costs to management practices in a firm, where managerial capital enters the production function, just like organizational capital does in

Table 1.7: Moments Used in the SMM Estimation

Parameter	**Symbol**	**Target Moment**	**Data**	**Model**
Growth Rate of A	γ	Average Growth Rate	21%	21%
Starting Value of A	A_0	Relative Size of Entrants	0.27	0.32
Skilled Labor - Output elasticity	μ	Share of Wage Bill going to Skilled Workers	0.29	0.30
Skilled Labor - Org Capital elasticity	θ	Change in Share of Skilled Workers between Age 0 and 5	-0.09	-0.083
Entry Cost	c_e	Survival Until Age 5	0.46	0.48
Exogenous Exit Rate	e	Probability of Exit	0.14	0.14
Reference Value for Organizational Capital Grid	Z_{Base}	Share of Skilled Workers in entrant firms	0.33	0.345

the model in this paper, to be higher than adjustment costs to physical capital. They state that this result is consistent with anecdotal evidence from the management consulting industry that managerial practices are at least as hard, if not harder, to change than establishment equipment. Both of these results do not speak directly to the estimated value of θ, however they do indicate that investment in organizational capital may be difficult and have high diminishing returns.

The model seems to fit the data fairly well. Panel A of Figure 1.8 shows the firm survival rate with age in the model and the data. The estimation of model parameters targets average exit rate and the percentage of firms that survive until age 5, and the model matches the remainder of the survival rate fairly well. Panel B of figure 1.8 depicts how the share of skilled labor in the firm changes with age in the data and in the model. The parameter estimation targets the share of skilled labor in entrants and the change in the share of skilled labor in the firm between age 0 and age 1. The model matched the rest of the decline in the share of skilled labor in the firm as they age fairly well, however, it fails to capture the tapering off of the decrease as the firms get past a certain age threshold. In the model, the share of skilled workers keeps decreasing as the firm ages, but it does so at a decreasing rate and it tapers off at a much later stage in the firm's life cycle.

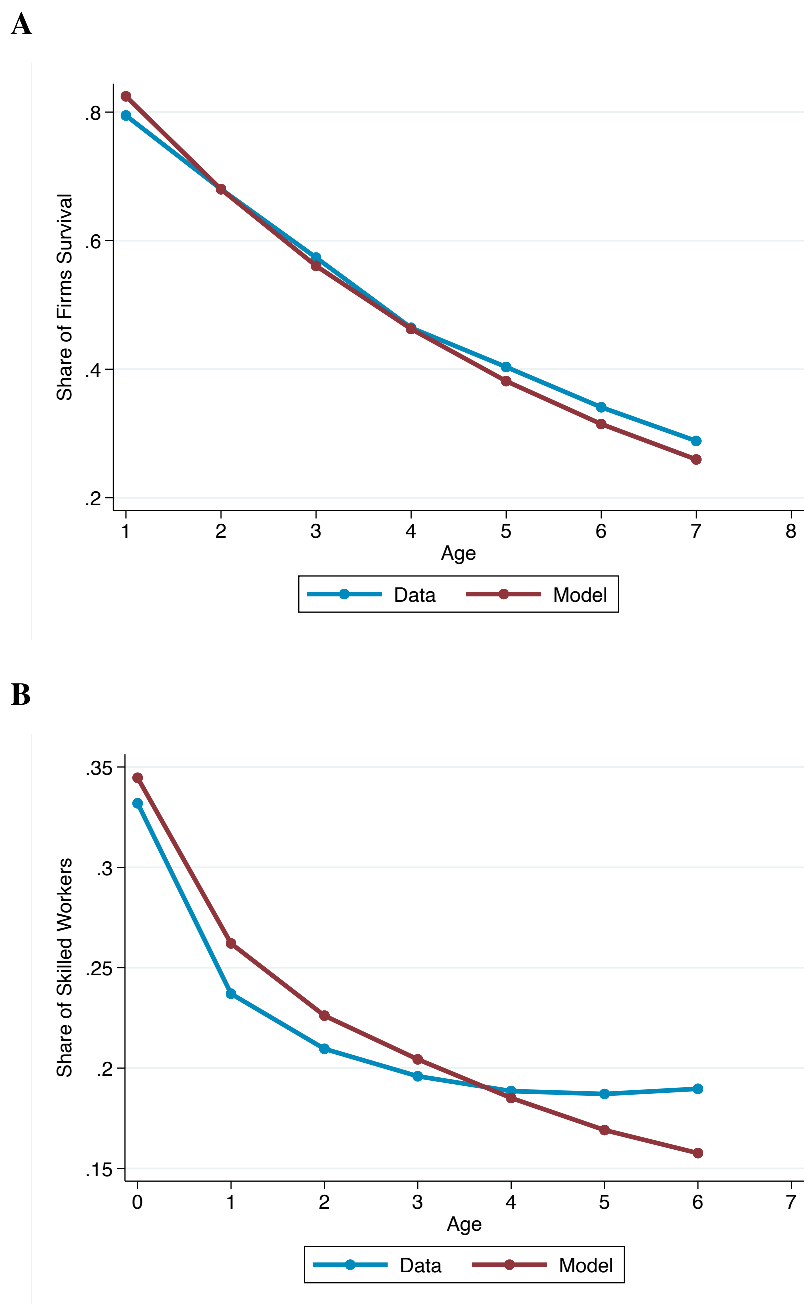


Figure 1.8: Model Fit: Survival Share and Share of Skilled Workers

Notes: figures comparing the **(A)** percentage of firms surviving until a given age and **(B)** the decline in the average share of skilled workers in the firm in the data and the model.

1.6.2 Organizational Capital and Firm Growth

Now that I have a calibrated model, I can address two questions. Firstly, I examine the share of the total firm wage bill that goes towards the workers who accumulate organizational capital. I find that in the model firms spend 25% of the total wage bill on organizational capital investment. The closest comparable estimate comes from Mouel and Squicciarini (2015), who find that the proportion of workers employed in the economy who are involved in organizational capital investment ranges from 16 to 25% across countries and the total expenditure on OC investment as a share of total value added of the economy ranges between 1.5 and 3.5% across countries, with significant heterogeneity across sectors. These estimates are not directly comparable to my measure, as I look at the share of the total wage bill and the measure of value added obviously involves not just the contribution of labor, but other factors of production as well.

In order to ascertain how much of firm growth comes from the accumulation of organizational capital, I perform a simple experiment with the calibrated model: I set $\gamma = 1$. This leaves firms with only one way to grow and that is to endogenously accumulate organizational capital. With $\gamma = 1$, all firms enter with the calibrated value A_0 and keep the same productivity level until they are hit with the random exit shock. I keep other parameters the same, except for the values of w_u and w_s that change to ensure that the model remains in equilibrium given N_u and N_s. Firms still enter with the initial value of organizational capital drawn from the distribution of Z_0 and they are still hit with the exogenous exit shock with the same probability. I find that the average growth rate of the firm defined as the average year-to-year difference in the log size of the firm decreases from **0.213** in the model with $\gamma = 1.05$ to **0.0609** in the model with $\gamma = 1$. This indicates that the accumulation of organizational capital alone can account for 28.5% of firm growth. To my knowledge, there are no comparable estimates in the literature to compare my estimate to, however the number is high and indicates that organizational capital is important to firm's growth. Based on the body of work of Bloom et al., who find in Bloom et al. (2016), for example, that differences in management practices can account for 30% in TFP differences across countries and across firms within countries, we know that managerial capital is an important determinant of firm performance. Organizational capital is not the same as managerial capital, but the two concepts do overlap, and the results of this paper suggest that organizational capital is also important in determining firm performance. The sample selection that I employed for the empirical results has also most likely played a role in the contribution of organizational capital to firm growth being high, as I a priori focus on successful firms that are likely to invest more in organizational capital and derive more benefit from it. Nonetheless, these firms employ around 50% of total employment and represent an important group of firms for overall economic well-being of Brazil. Organizational capital has gathered a lot of attention in the management literature, but has not been modeled extensively in macroeconomics. Nevertheless, given that my model indicates that it accounts for **28.5%** of firm growth, it is an important source of firm growth and should be part of a larger investigation in the role of knowledge-based capital accumulation in firm performance.

1.7 Conclusion

In this paper, I propose a tractable model of organizational capital accumulation that I use to examine the role of organizational capital in firm growth. Organizational capital is a type of knowledge-based capital that is best described as firms' codified and tacit knowledge about themselves and their environment: standards, production procedures, "codes, technical languages, practical arrangements about how the work is done and the creation of an organizational culture" (Gomes (2007)). Based on previous research into the nature and ways of accumulating organizational capital, I link organizational capital in the firm with its demand for skilled labor, arguing that only skilled labor can successfully invest in organizational capital. I present a simple model of industry dynamics where there is both exogenous and endogenous growth. Exogenous growth stems from exogenous increase in firm productivity, whereas endogenous growth stems from the firm accumulating organizational capital. I then present novel empirical evidence that shows that as firms grow older and bigger, the average skill level of the firm's workforce decreases. I use this relationship to calibrate the model and examine how much firms invest in organizational capital and how much of firm's growth stems from organizational capital accumulation. I find that firms spend 25% of their total wage bill on organizational capital investment and that organizational capital can account for 28% of firm growth, making it an important determinant of firm growth and firm performance.

Chapter 2

Firm Size-Wage Premium Revisited

2.1 Introduction

Firms are the main place of employment for a large share of the workforce and the main vehicle of economic activity. As firms face changes in their environment, which subjects them to productivity or demand shocks, or simply go through their life cycle, they make decisions about which workers to hire and which workers to keep. As workers differ in their level of skill and what they can contribute to production as well as their fit with the firms, the composition of the workforce in the firm is not random. Understanding how firms organize their workforce and what mix of skills they require at different stages of their development together with the evolution of the age and size distribution across time is essential towards understanding the recent trends in wage inequality and differential employment for different workers. Significant progress in the theory of firm organization has been made following the suit of Garicano (2000), which started the wave of using the insights about within-firm organization to re-interpret recent trends in economic activity with this information in mind. At the same time, the wider availability of firm-level and worker-firm matched datasets has enabled the recent push in documenting how

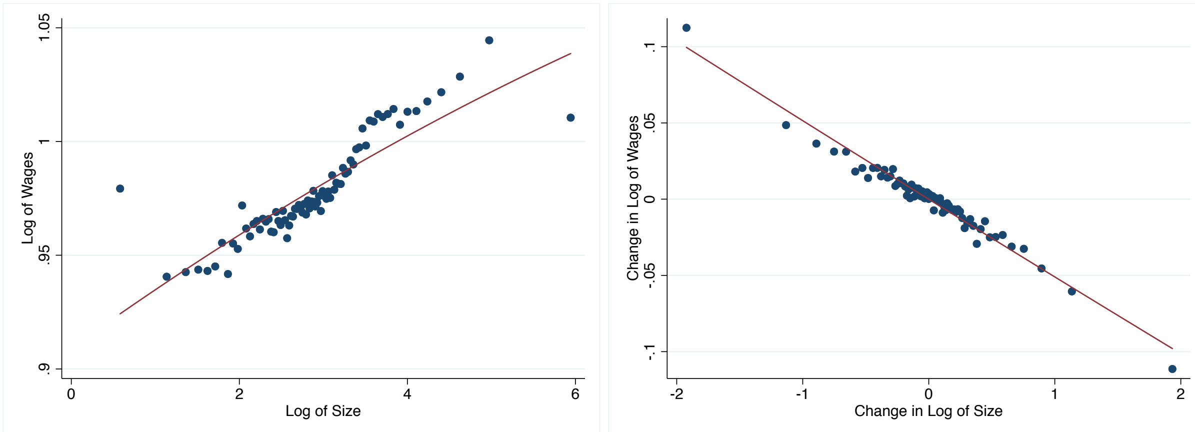


Figure 2.1: Wages & Firm Size: Levels and Within-Firm Changes.

Left: the relationship between firm size and average wage in the firm, both in logs. Right: The relationship between the change in log of firm size and the change in the log of average wages. Both bin scatter plots include the following controls: year, region, industry and age FEs.

firms organize their workforce and how they respond to shocks [1], but empirical evidence on what happens in the organization of firms as they grow and expand is still lacking. This paper looks to contribute to the empirical evidence on firm organization by looking at what happens to average wages and worker composition withing the firm as firms expand.

Consider Figure 2.1. The left panel of Figure 2.1 shows how average wages within firms change with firms size in the cross-section, whereas the right panel of Figure 2.1 shows the relationship between the within-firm change in average wages and the change in firm size, where size is the number of employees. In the left panel, we see a confirmation of firm size - wage premium in Brazil, but the right panel shows that as firms get bigger, they pay on average lower wages to their workers. Mechanically, the negative correlation between the change in the firm size and the change in the average wages in the firm can arise from two source. The wages for the workers could fall on average, so, assuming that firms pay workers based on their contribution to production, the firm pays less per one unit of effective labor as it expands. Instead, or in addition, the firm's demand for skill could alter in such a way that it demands

[1] see, for example, Caliendo et al. (2015b) for France or Caliendo et al. (2015a) for Portugal

disproportionately more of the relatively lower skilled workers as it expands.

I find the latter in my data: the negative relationship between size and wage in the firm life cycle can be explained by the changing composition of the workforce as firms expand. In particular, firms grow in size by hiring mostly lower paid and lower skilled workers, which pushes down the average wages within the firm. In order to study how the firms adjust their worker composition, I divide the workers into three groups based on their educational attainment. I find that when firms grow, they do so by mostly hiring less educated workers. However, even within the education groups, the average wages fall as firm size increases, implying that the disproportional hiring of low-skilled workers persists within education groups as well. On top of the coarse categorization based on educational attainment, I also perform regressions with worker-level fixed effects to control for innate ability, together with firm tenure and educational dummies to control for acquired skill. I find that when controlling for worker fixed effects, the change in firm size is associated with an increase in wages, implying that, if anything, as firms grow they are willing to pay more per one unit of skill. This further indicates that the source of reduction in average wages associated with firm growth is due to the change in worker skill composition.

I further examine how exactly firms adjust the composition of their workforce by looking at the change in wages and the composition of the new hires and the workers that remain employed in the firms since the year before. I find that with each new expansion the average wages for newcomers fall. The same pattern, but much weaker is present for previously employed workers as well, hinting at the fact that firm expansion is not a simple affair of bringing new workers in, but is also accompanied by some reorganization of the already employed workforce. However, the contribution of the new hires to the overall change in the composition of the workforce is more significant than the reorganization of already employed workers. Finally, I examine how it is possible that even though as firms grow the average wages fall, bigger firms still have higher wages in the cross-section. I find that firms that start with higher wages end up growing significantly larger than the firms that start with lower wages.

The paper contributes to several strands of literature. First and foremost, it contributes to the empirical literature on firm organization. I find that average wages go down as firms expand due to the reorganization of the workforce towards lower skilled workers. Several other papers come to similar conclusions using smaller datasets. For example, Garicano and Hubbard (2007) find that as law firms grow, the ratio of partners to associates decrease, and Caroli and Van Reenen (2001) find that as firms decrease employment the wage bills of different skill categories change disproportionately using a small panel of French and English firms. Caliendo et al. (2015b) find that as firms expand, the number of hours worked by lower-level employees relative to the number of hours worked by the higher-level employees increases using a large sample of French manufacturing firms. I find a similar pattern in Brazil among a subset of high-performing firms using wages and the shares of workers of different skill for inference. I am also able to control for worker fixed effects, which allows me to better distinguish the change in the price of skill from the change in the demand for skill as firms expand. Caliendo et al. (2017) find that as firms reorganize when they become exporters they do so by adjusting the average education attainment in the organizational layers of the firm. I look at educational groups to determine skill, but also supplement my analysis using worker-specific fixed effects.

The paper also contributes to a vast literature that examines the wage premium that workers enjoy in large firms. All of my regression specifications find a positive wage premium in Brazil, but it is rather small, consistent with the finding of a small size-wage premium in Even and Macpherson (2012). I also find a differential size-wage premium across education groups, implying that skill premium increases with firm size, just like Mueller et al. (2017) do for the UK. Beyond confirming the size-wage premium, I explore how it arises mechanically. I find that initial size and wages are strongly positively correlated with the future size of the firm.

The rest of the paper is organized as follows. Sections 2 and 3 discuss the data and its limitations, as well as the empirical strategy that I employ. Sections 4 and 5 presents the evidence of the change in worker composition as firms expand for all workers and for the new hires and stayers respectively. Section 6 discusses the issue of firms growing relatively large if they start with higher wages and Section 7 concludes.

2.2 Data

I am using the *Relação Anual de Informações Sociais* (RAIS) dataset, which is a yearly administrative employee-employer matched panel dataset from Brazil for both private and public workers in the formal sector. The main unit of observation is a worker, and the dataset contains a wide range of demographic characteristics, such as age, race, sex and years of schooling, as well as detailed occupation information and tenure at the firm measured in months. The compensation data is reported in reals per month, and includes salary as well as other benefits. Starting in 1994 I also observe the number of hours worked per week, which allows me to construct real wages for workers.

A potential problem with using the RAIS dataset to study firm dynamics is the fact that it only collects data on formal workers in formal firms, which presents two problems. Firstly, there is the issue of informal firms. As noted in (Ulyssea, 2018), around 30% of workers in Brazil are employed in informal firms[2]. To an extent that the choice to formalize is not random and can be correlated with the wage setting policy and personnel choice in the firms, the exclusion of informal enterprises presents a source of bias when estimating how firms change the composition of the workforce and the wage-setting policies as they expand. However, it is also the case that informal firms tend to be small in Brazil [3]. For the main analysis presented further, I consider firm with on average 3 employees throughout their life cycle, which leaves me with around 45% of the sample[4] .

[2]To my knowledge, no convenient statistic on the proportion of informal enterprises in Brazil is available.

[3]Ulyssea (2018) documents that the probability of a firm being informal decreases sharply with size, with fear of greater visibility being the possible reason

[4]The results carry through with other size cutoffs as well, as presented in the Appendix

In this paper, I study the composition of the workforce in terms of the share of workers with different levels of educational attainment. I divide the sample of workers into three education categories:

- $PM+$, which includes people who have only finished primary school;
- $HS+$, which includes people with a high school diploma, and who may have started but not finished college;
- $Coll+$, which includes people with a bachelor's degree or above;

By construction, each worker can belong only to one of these groups at a time. From now on, I will be using these groups to talk about firm-level regressions and results. I use educational attainment as a proxy for the skill level of workers, with the assumption that educational attainment conveys some information about the skill of the worker as perceived and used by the firm. This assumption is not innocuous. It is possible that in a context such as Brazil, where education attainment is in general low, especially with regards to college education, it is a poor signal of skill, and there are other characteristics, unobserved to the researcher, that inform potential employees about the skill of a given worker and influence their decision to hire the worker and give them a certain wage. There are many alternatives to dividing workers into categories in the workforce. Mueller et al. (2017) use a skill classification employed and designed within the firm itself, where workers are explicitly divided into skill groups, mostly based on the type of occupations that they have. Others have divided occupations into managerial and non-managerial or cognitive and routine and examined the wages of workers in these categories Autor et al. (2003). These are all valid alternatives to my approach and can result in productive inquiry into how the composition of the workforce changes as firms expand. An advantage of using educational attainment as a first step of analysis is that the categories are clear cut and marked with official diploma that are easily interpretable for both the firm and the researcher.

Table 2.1: Summary Statistics: Education Categories

	Prim		HS		Diff	
	Mean	SD	Mean	SD	Mean	SD
Log of Wage	0.17	0.52	0.48	0.58	1.57	0.89
Hours (weekly)	43	4.2	42	4.2	40	4.4
Share of Sample	0.51		0.41		0.08	
N	15,794,605		12,725,910		2,257,214	

Table 2.1 provides summary statistics on average wages and contractual weekly hours across the three education categories. There is a clear increasing relationship between the level of educational attainment and the wage, which can be interpreted as evidence that the skill classification based on the level of education that I use does convey some information about what the workers end up doing in the firm and how the firm perceives their skill level. It is also important to note that Coll workers make a very small share of the total sample, only 8%, which reflects the lower educational attainment in Brazil.

I follow each firm from inception throughout its life cycle. I keep every worker in the firm, regardless of their demographic characteristics, in order to get a representative picture of the composition of the workforce in the firm and the wages paid to the workers. As a large portion of analysis has to with wages, I limit my attention to years 1994 to 2014, so I only consider firms born in 1994 or later. I exclude government, health and education firms because the notion of a firm is not so well defined in their case. The results carry through when I consider only manufacturing or service firms.

In line with Chapter 1 of this dissertation, where I restricted my attention only to high performing firms in order to keep the sample in line with the model, in this chapter I restrict my attention to firms that hire at least one college educated workers when they enter the market. This again leaves me with 21% of the firms that employ around 50% of the workforce in the full sample.

Table 2.2: Summary Statistics: Firm Level

	Born Without Coll		**Born with Coll**		Difference	
	Mean	SD	Mean	SD	Diff	t-stat
Log of Size	1.71	0.69	2.70	1.20	-1.00***	(-313.95)
Log of Wage	0.11	0.44	0.91	0.71	-0.80***	(-415.98)
Age of Exit	5.71	6.34	6.62	5.49	-0.91***	(35.17)
Prim Share at Birth	0.74	0.38	0.25	0.30	0.49***	(560.05)
HS Share at Birth	0.26	0.38	0.44	0.29	-0.18***	(-215.92)
Coll Share at Birth	0.00	0.00	0.31	0.28	-0.31***	(-424.85)
Prim Share	0.69	0.36	0.25	0.28	0.44***	(536.67)
HS Share	0.29	0.35	0.48	0.26	-0.19***	(-244.54)
Coll Share	0.01	0.06	0.27	0.25	-0.25***	(-395.84)
N	772,161		152,689		924,850	

These firms are not a representative sample of firms in Brazil, but they present an economically significant group. Figure 2.2 shows that these firms have higher wages and are bigger at every point in the distribution. Table 1.3 confirms that the firms that I call "high-performing" pay on average higher wages, are on average larger and survive for longer. In addition, it shows that the firms in my sample have higher shares of workers in the HS and Coll category, which are the higher skill categories in my interpretation, both at birth (by construction) and throughout their life cycle as well. We can also see that even for the firms in my restricted sample, Coll workers make only a quarter of the entire workforce, which is most likely motivated by a low share of Coll workers in the labor force in Brazil. Appendix B presents the empirical results for the full sample of firms.

2.3 Empirical Strategy

The paper examines the relationship between average wages within the firm and firm size and what it says about how firms choose who to employ using two approaches. Firstly, I use

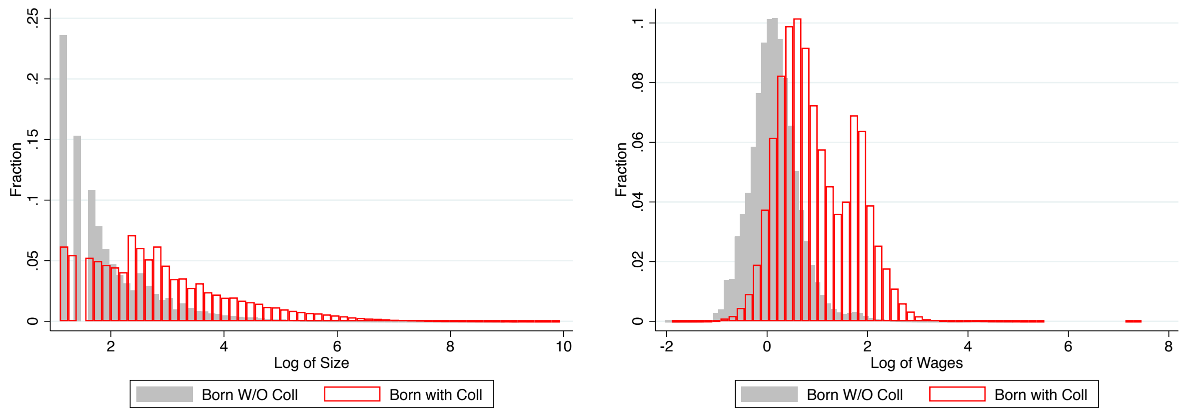


Figure 2.2: All firms vs. "Well-performing" firms

Left: Distribution of log of firm size measured as number of workers in firms that hire college educated workers when they enter versus firms that do not hire any college educated workers when they enter. Right: Distribution of log of wages in the two samples of firms.

firm-level regressions to assess the relationship between average firm quantities. The firm-level regression specifications are as follows:

$$\mathrm{y}_{ft} = \beta \mathrm{LogN}_{ft} + \alpha_t + \alpha_r + \alpha_{age} + \alpha_{ind} \quad (+\alpha_f) + \varepsilon_{ft}$$

where y_{ft} is either the average wages in the firm, overall or of a particular education group,[5] or the share of workers of a particular education group. The two specifications both have year, region and firm age fixed effects, but differ in the last set of fixed effects. The *cross-section* specification includes only industry-level fixed effects, whereas the *life cycle* specification includes firm-level fixed effects. In this way, the cross-section specification identifies the relationship between average firm wages and firm size using the variation across firms of the same age in the same year, region and industry, whereas the life cycle specification uses the within-firm change in wages and size as the source of variation. The main coefficient of interest is β, the coefficient on the log of size.

The second approach is an individual-level regression and is used to reinforce the findings

[5] So, y_{pt} is overall average log of wages or average log of wages for each education group separately

of the first approach. The regression specifications are as follows:

$$\begin{aligned}\text{logwage}_{it} =& \beta_1 \text{LogN}_{ft} + \alpha_{educ} + \beta_2 \text{LogN}_{ft} \times \text{HS} + \beta_3 \text{LogN}_{ft} \times \text{Coll} \\ &+ \alpha_{exp} + \alpha_{race} + \alpha_{sex} + \alpha_r + \alpha_t + \alpha_{ind} \quad (+\alpha_f) \quad (+\alpha_i) + \varepsilon_{it}\end{aligned}$$

For the worker-level regressions, there are three specifications: cross-section, life cycle and "Mincer" that yet again differ by a set of fixed effects. In all regressions, I control for demographic variables, such as race and sex, and tenure at the firm, together with education and firm-level characteristics, similar to the first approach. The cross-sectional and the life cycle specifications follow the same logic as the respective specifications for firm-level regressions, with industry and firm fixed effects respectively. The "Mincer" specification includes both the firm- and the worker-level fixed effects. In this case, the identifying variation comes from firms expanding and workers changing jobs. This allows me to control for unobserved worker characteristics that affect the workers' wage and are constant across time. With the "Mincer" specification, I do my best to eliminate the workforce composition element from the effect of the change in size on the change in average wages, because I keep the innate worker ability level constant and control for educational attainment as well as tenure at the firm. The latter two control for the increase in skill that is gained through education and through the accumulation of firm-specific human capital from time spent on the job. If the results of the within-firm individual-level regression and within-worker individual-level regression differ, then I can identify the change in the composition of the workforce separately from the change in the price of one unit of skill that are associated with a firm's expansion, hence fully decomposing the source of the change in the average wage.

The coefficients of interest are β_1, the coefficient on the log of size, as well as β_2 and β_3, the coefficients on the interaction between educational attainment and size, where Prim is the base education group. The latter two allow to examine whether there is differential firm-size wage premium for workers of different skills, as well as whether the wage changes that are present when firms expand are the same across education groups.

2.4 Firm Wages and Firm Size

We start with the average wage and firm size regressions. The results are presented in Table 2.3. The first column demonstrates the well-established positive, albeit small in this case, relationship between firm size and average wages within the firm in the cross-section. Even though the continuous relevance of the firm size - wage premium is being debated (for example, see Bloom et al. (2018)), it is still present in this sample. In the cross-section, bigger firms pay slightly higher wages. Of more interest are the results of the life cycle specification, where with the addition of firm-level fixed effects in the regression the relationship between average wages and firm size becomes negative. As firm hire more workers, the average wage in the firm falls. The magnitudes may seem small, but they are economically meaningful. A 100% increase in the number of workers employed at a firm is associated with a 5% decrease of average wages in the firm. Given that the smallest firm in my sample has three workers a 100% and more increase in firm size is possible.

Figures 2.3 and 2.4 further investigate the life cycle negative relationship between firm size and average wages within the firm. The left panel of Figure 2.3 present the β coefficient in the Life Cycle firm-level regression with 95% confidence intervals, where a separate regression is run for firms by exit age. We see that even though the magnitude varies, the negative relationship is still present regardless of how long the firms survive for.

I then consider whether this negative relationship between firm size and firm wages throughout the firm life cycle is driven by firms at the early stages of their life or are present throughout their existence. I divide the firms into 5 age groups, each 3 years long. So firms in Age Group 0 are firms aged 0-3, firms in Age group 1 are firms age 4-6, and so on, with Age Group 5 consisting of firms that have been in the market for 16+ years. I run the life cycle

Table 2.3: Log of Wages & Size

	Ind FE	Firm FE
Log of Size	0.011**	-0.053***
	(0.004)	(0.008)
Constant	0.099***	0.244***
	(0.08)	(0.04)
Observations	153,696	153,696
R-squared	0.350	0.860
Year FE	Yes	Yes
Region FE	Yes	No
Industry FE	Yes	No
Firm FE	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

regression in each age group to see if the negative relationship between average wages and firm size is more pronounces among young firms. The results are presented in the right panel of Figure 2.3, where each dot represent the β coefficient in the life cycle regression run for firm in the particular age group only. We can see that the relationship is the strongest when I run the regression for young firms only, and then somewhat tapers off when I consider older firms.

The same patterns can be seen more clearly in Figure 2.4, where the life cycle regressions are run by each group using a balanced panel of firms. The left panel presents the results for firms that exit when they are 12 and the right panel presents the results for firms that exit when they are 16. This allows me to ascertain whether the results described in the right panel of Figure 2.3 are present within a firm's life cycle or are instead dominated by the selection of firms into different age groups based on unobserved characteristics. If firms that makes it to Age Group 4 (age 10-12) are different in meaningful ways from firms who exit after 3 years of operation, then it might be these unobserved differences that drive the change in the relationship between firm size and wages across the age groups, rather than the differences in firm behavior across its life

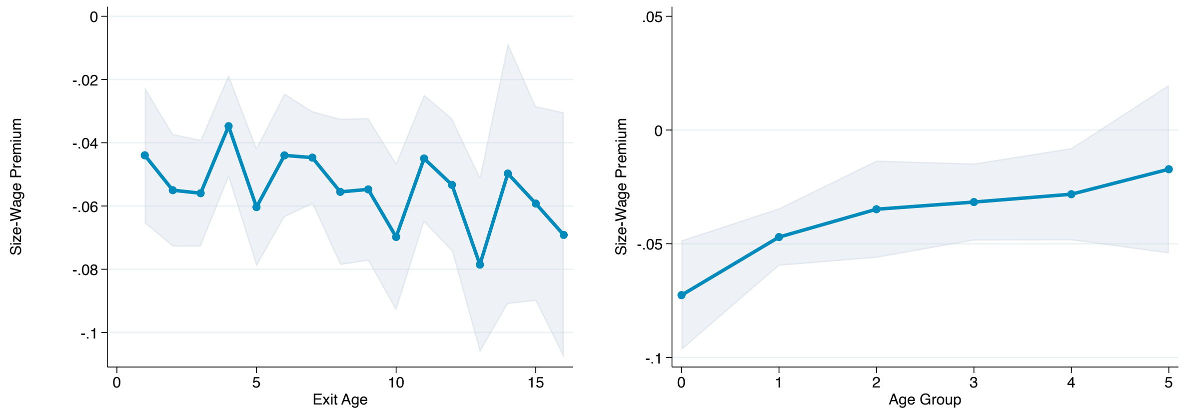


Figure 2.3: Wages and Size in the Life Cycle: Results by Exit Age and Age Group

Notes: Each dot in the graph represents a coefficient in the regression of the average wage in the firm on the fixed effect of age and firm-level FE, with 95-% confidence interval. Left: Separate regressions are run for firms that exit at the specified age. Right: Separate regressions are run for firm in 3-year long age groups.

cycle. Figure 2.4 shows that this is not the case. We see the same increasing pattern across age groups for firms that survive until the age of 12 and the firms that survive until the age of 16. It is in the earliest stages of the firm's life that wages decrease the most as firms expand.

The results presented above are somewhat puzzling. On the one hand, bigger firms do offer higher wages, but on the other hand if we follow a single firm, average wages fall as firm size increases. If we compare a small firm to a bigger firm, the bigger firm will most likely have higher wages on average. However, the results presented above suggest that as the eventually larger firms grew in size, their average wages most likely decreased. Mechanically, this means that the starting wages in the firms that ended up growing comparatively large were higher than the wages in the firms that end up comparatively small. Indeed, I find that wages together with the share of high-skilled workers at birth are predictive of future size, with firms that start with higher wages ending up larger as they age. I will briefly discuss this point in the last section of this Chapter.

What is driving this decrease in average wages as firms expand? As mentioned before, average wages can go down as firms expand for two reasons: either wages decrease for everyone

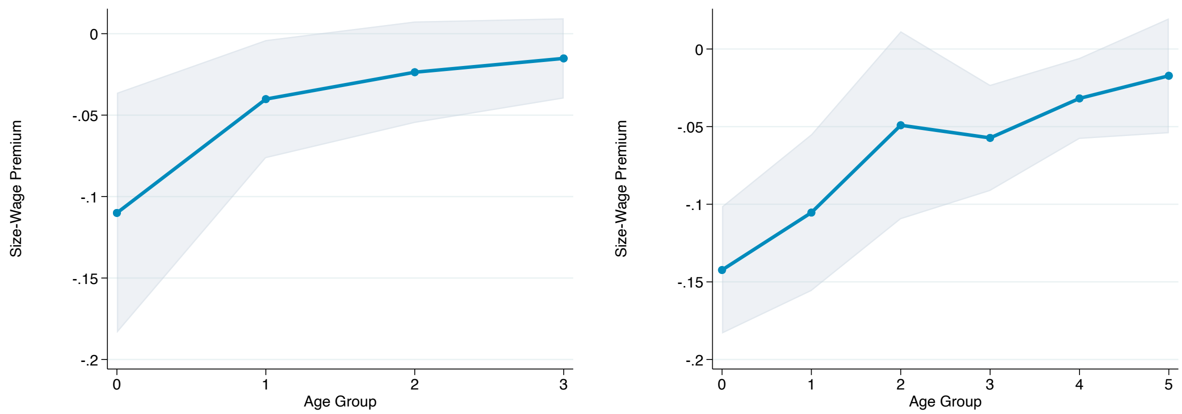


Figure 2.4: Wages and Size in the Life Cycle: Age Group Results in the Balanced Panel

Notes: Each dot in the graph represents a coefficient in the regression of the average wage in the firm on the fixed effect of age and firm-level FE, with 95-% confidence interval. Left: Separate regressions are run for firm in 3-year long age groups, with the sample of firms that survive until the age of 12. Right: Separate regressions are run for firm in 3-year long age groups, with the sample of firms that survive until the age of 16.

as firms expand or the newer workers that firms higher are lower paid. The newly hired workers can be paid less because the firm pays the newcomers less for the same amount of effective labor that they supply or because the firms expand primarily by hiring lower skilled workers who do not supply the same amount of effective labor. In order to disentangle the two possibilities, I will first examine how the composition of the workforce changes as firms expand by dividing the workforce into the three educational categories outlined in the previous section.

Consider Figure 2.5. The left-hand side panel depicts the binned scatter plot of the shares of workers in each of the education groups against the log of size. We see a strong negative relationship between firm size and the share of Coll workers, who I assume to be high-skilled. In this sample, bigger firms have a different composition from smaller firms, where they have disproportionately fewer Coll workers. The right-hand side of Figure 2.5 depicts the binned scatter plot of change in shares of workers in each category against the change in log of size. Yet again, there is a strong negative relationship between firm expansion and change in the share of high-skilled workers. As firms expand, they do so by disproportionately hiring workers from lower education categories and/or by reorganizing their existing workforce in such a way that

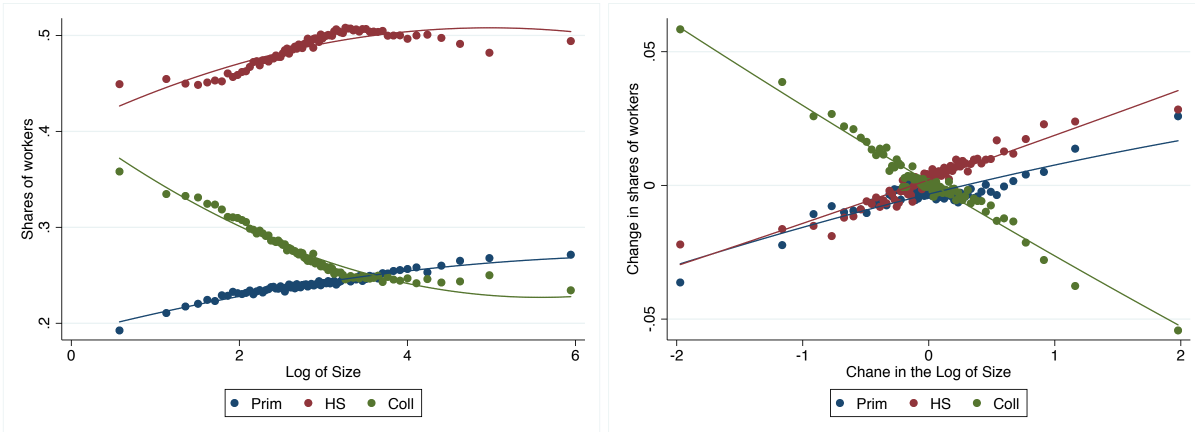


Figure 2.5: Share of Workers by Education Group & Size: Levels and Within-Firm Changes

Left: the relationship between firm size and share of workers by different education groups in the firm. Right: The relationship between the change in log of firm size and the change in the share of workers by different education groups in the firm. Both bin scatter plots include the following controls: year, region, industry and firm age FEs.

the share of low-skilled workers goes up.

Table 2.4 presents the findings outlined in the Figure 2.5 in regression form. The coefficients for the three education categories within each specification have to add up to 0 because the three worker types are exclusive. From the cross-section specification that is presented in the three leftmost columns of the table we can see that larger firms have proportionately fewer Coll workers. This result is the artifact of the restricted sample that I use. If firms start with high-skilled workers already, they have less room to add more high-skilled workers than if they started with no high-skilled workers. Indeed, if we look at the full sample regression results that are presented in Table B.2 in the Appendix, we see that bigger firms do indeed have proportionately more Coll workers, as one would expect in Brazil . This peculiar feature of my restricted sample can explain the relatively low firm size - wage premium found in Table 1.4 as larger firms in this restricted sample have a relatively low share of Coll workers as compared to smaller firms. Nonetheless, both in the full sample and the restricted sample as firms expand, they do so by disproportionately favoring lower skilled workers. This provides the first piece of evidence that as firms expand they change the composition of their workforce that results in the reduction

Table 2.4: Change in Shares with Change in Size

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.015***	0.027***	-0.042***	0.027***	0.03***	-0.057***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)
Constant	0.35***	0.31***	0.35***	0.24***	0.38***	0.39***
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
N	153,696	153,696	153,696	153,696	153,696	153,696
R-squared	0.56	0.32	0.51	0.87	0.75	0.83
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

of average wages.

Now that we have examined what happens to the shares of workers in each education category, we can examine whether there is change in the workforce composition beyond the three groups that I outlined. Consider Table 2.5. It presents the results of separate regressions of average wages within each education category on firm size. The results paint a picture similar to the average wage regression. In the cross-section, there is a positive relationship between average wages and firm size, and the coefficient is higher for the Coll workers, indicating a presence of rising skill premium with firm size, consistent with Mueller et al. (2017). As far as the within-firm specification goes, we can see that there is a decrease in average wages associated with the increase in the firm size within each group. The combination of the cross-section and the within-firm results provides evidence for the following process of firm size and wage evolution. Bigger firms do have higher wages on average, for all education groups but mostly so for the college educated workers. However as firm get bigger the average wages fall, not only overall, but within each education category as well. The change in the shares of workers in each educational

Table 2.5: Log of Wages by Groups

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.04***	0.04***	0.06***	-0.01***	-0.02***	-0.014***
	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)	(0.004)
Constant	-0.271***	-0.274***	1.155**	0.050	0.200***	-0.045
	(0.039)	(0.045)	(0.561)	(0.058)	(0.056)	(0.622)
N	110,542	136,134	125,794	110,542	136,134	125,794
R-squared	0.350	0.348	0.289	0.784	0.821	0.827
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

group as firm expand would account for the average wages falling as firm hire new workers, but not for the fact that average wages within each category also fall as firm size increases. This would be the case if firms hired lower skilled workers within each category as they increased their workforce, which is a distinct possibility given that educational attainment captures only part of the skill that is relevant for the firm. I now turn to examine this hypothesis.

To eliminate potential confounds that affect wages (such as workers' tenure at the firm), I turn to the individual-level regressions. The results presented in Table 2.6 give partial confirmation of the results of the firm-level regressions presented before. We still observe a positive relation between firm size and wages in the cross-section, and the sign of the coefficient on log of size again flips when firm-level fixed effects are included. We also observe an increase in wages with increase in educational attainment, yet again indicating that the three educational categories convey meaningful information about skill that is recognized and rewarded differentially by the firms. Interestingly, there is no concrete evidence of there being differential effects between Prim and HS workers in regards to how their wages change as firms expand: the interaction coefficient is not significantly different from 0. For the Coll workers, the firm expansion

Table 2.6: Mincer Regression

	Ind FE	Firm FE	Worker FE
Log of Size	0.03***	-0.02***	0.02***
	(0.01)	(0.01)	(0,005)
HS	0.40***	0.21***	0.22***
	(0.06)	(0.03)	(0.05)
Coll	0.84***	0.53***	0.55***
	(0.11)	(0.09)	(0.06)
HS × Log of Size	-0.03***	-0.01	-0.02**
	(0.001)	(0.004)	(0.01)
Coll × Log of Size	0.02	0.04***	-0.01
	(0.014)	(0.01)	(0.01)
Constant	0.51*	0.98***	0.79***
	(0.28)	(0.23)	(0.19)
Observations	39,455,138	39,455,138	39,455,138
R-squared	0.64	0.75	0.95
Year FE	Yes	Yes	Yes
Region FE	Yes	No	No
Industry FE	Yes	No	No
Firm FE	No	Yes	Yes
Worker FE	No	No	Yes

Notes: Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

leads to a smaller fall in the average wages.

The negative coefficient in the second column of the table confirms that even with additional controls, on average firms that grow bigger see their average wages fall. Important evidence alluding to what might be going on comes from comparing the second and the third columns of the table. With the inclusion of both worker-level fixed effects and firm-level fixed effects, the identifying variation comes from both firms changing size and workers switching employment, which allows to eliminate the worker-specific constant ability. Together with firm tenure and education level, using worker-level fixed effects controls as much as possible for any component of skill, keeping worker composition effectively constant. The fact that we see a significant positive coefficient in the worker-level regression means that, controlling for worker composition, as firm expand they pay higher wages to the same worker. This provides evidence that the fall in the average wages associated with firm expansion discussed above is mostly due to the change in the composition of the workforce. It seems that as firms grow their workforce changes in such a way that the average skill level of the workers declines. Now it is possible that this change in the workforce composition is mostly accomplished by adding new low-skilled workers, or by nonrandom changes in the composition of already employed workers that is brought on by firm expansion. In the next section I provide tentative evidence that it is mostly the addition of new low-skilled workers that brings about the decrease in average wages as firms expand.

2.5 New Hires VS Stayers

The previous section has established that the decline in average wages as firm expand is mostly due the change in the composition of workers. Indeed, a positive change in size is associated with a positive change in the wages for workers once I control for individual-level fixed effects. In this section, I consider whether the change in the composition is driven by the addition of low skill workers to the firm as it expands or by reorganization of already employed workers.

I perform the firm-level and the individual-level regressions described above for two groups of workers in a firm in each given year: the new hires, the workers who have just joined the firm, and the stayers, the workers who have remained with the firms since last year. This analysis is designed to further identify the source in the change of average wages with firm size change. Just like in the case of individual-level regression described above, the comparison between the three specifications will allow me to see if in the case of both new hires and stayers the wages actually change on average or if the composition of the workers changes in a non-random way. The average wages for the newcomers can change if the firm pay lower wages to people with the same skill level if they join the firm when it is bigger or if the new hires are lower skilled than the people that the firm hired during its previous expansion. The same analysis for

Table 2.7: New Hires and Stayers Wages: Average

	New Hires		Stayers	
	Ind FE	Firm FE	Ind FE	Firm FE
Log of Size	0.02**	-0.05***	0.03***	-0.03***
	(0.006)	(0.010)	(0.01)	(0.01)
Constant	0.256*	0.550***	0.241***	1.026***
	(0.145)	(0.043)	(0.06)	(0.03)
Observations	132,751	132,751	121,422	121,422
R-squared	0.32	0.77	0.35	0.86
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

the stayers will indicate whether a firm expansion is associated with internal reorganization of the already employed workers. All regressions use clustered standard errors at the industry level.

Below, I present the results of the cross-section, life cycle and "Mincer" regressions for two separate groups of workers: new hires and previously employed workers (stayers). If there is a significant change in the average wages of stayers as firms expand, then the addition of new workers may be associated with internal firm reorganization and change in the composition of previously employed workers, as well as with the addition of new workers that may already be significantly lower skilled than the stayers.

Table 2.7 presents the results of the firm-level regressions, where the dependent variable is the average wages of either new hires or stayers in a given firm in a given year. The two leftmost columns deal with new hires. We can see that, just as was the case with the average wages for all workers, bigger firms do offer higher starting wages. However, from the firm-level regression we can see that as firms get bigger, their average starting wage decreases. Just like in the previous section, this can mechanically be attributed to two possibilities. On the one hand, as firms expand, they might be hiring people of the same skill level, but paying them less. A possi-

Table 2.8: Change in Shares for New Hires with Change in Size

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.02***	0.01 ***	-0.03***	0.03***	0.02***	-0.05***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.008)
Constant	0.38**	-0.09	0.71***	0.27***	0.09	0.65***
	(0.16)	(0.07)	(0.22)	(0.05)	(0.15)	(0.19)
Observations	132,748	132,748	132,748	132,748	132,748	132,748
R-squared	0.28	0.16	0.25	0.62	0.52	0.59
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

ble explanation for that is that workers that join smaller firms might need to be compensated with higher wages if the continuous survival of the smaller firm is less likely than continuous survival of a larger firm, which would lead to a decrease in starting wages as firms expand. Another possibility is that firms hire lower skilled workers with each subsequent expansion. Interestingly, we see a similar pattern among the stayers. The results in the rightmost column state that as firms expand, stayers in the firms see their average wages fall: it seems that a firm expansion is associated with a decrease in average wages for previously employed workers. This implies that either wages on average fall for the stayers, or that they also undergo a change in composition, with higher skilled workers more likely to leave the firm or low-skilled workers more likely to be retained, as in the case with stayers the mechanism for changing worker composition is laying off certain workers. These results might indicate that firms undergo restructuring upon every expansion which affects not only who they decide to hire but who they decide to keep and who they decide to let go.

Tables 2.8 and 2.9 present the results of the regression of shares of workers in each educational category on firm size for new hires and for stayers. For clarity, consider the case of

Table 2.9: Change in Shares for Stayers with Change in Size

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.02***	0.01***	-0.03***	0.01***	0.02***	-0.03***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
Constant	0.41***	0.29***	0.30***	0.49***	0.06	0.45***
	(0.024)	(0.023)	(0.030)	(0.050)	(0.049)	(0.040)
Observations	155,214	155,214	155,214	155,214	155,214	155,214
R-squared	0.33	0.18	0.26	0.76	0.67	0.71
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

the share of Coll workers among new hires. The share represents the proportion of new hires who fall into the Coll category out of all the new hires. Table 2.8 shows that bigger firms tend to hire disproportionately more low-skilled workers. The results in the three leftmost columns of Table 2.8 imply that when bigger firms hire a new worker, the new worker is more likely to be of lower skill than if a small firm hires a new worker. The results presented in the three rightmost columns of Table 2.8 indicate that with each new expansion, firms add more low-skilled workers than they do high-skilled workers, compared to their previous expansion. As the identifying variation for the within-firm regression comes from the changes in size and shares of different educational groups of new hires for the same firm, the results mean that when firms decide to expand, they do so by mostly hiring low-skilled workers, and the propensity to disproportionately hire low-skilled workers increases with size.

Table 2.10 considers whether on top of change in the composition among education group, firms also hire lower paid workers within education groups as they expand. It considers the average wages in each education group and how they relate to firm size. We see that in the cross-section, bigger firms do offer higher starting wages to workers in each category. With regards to the within-firm regression, the results are somewhat less convincing than in the case of average wages for both stayers and new hires, as the coefficient on the Prim workers' wages is not significant and the coefficient on the Coll workers' wages is marginally significant. This suggests that the change in the skill level of new hires contributes significantly to the decrease of average wages as firms expand, and based on the firm-level regressions a lot of the effect comes from changing the composition of workers among education groups, as opposed to relying on a more granular definition of skill and switching to lower paid workers within education categories.

When considering stayers, surprisingly, the results concerning the shares presented in Table 2.9 are very similar to the results concerning new hires presented in Table 2.8. Table 2.9 suggests, first of all, that bigger firms have disproportionately more low-skilled workers when we ignore who they decide to hire and focus on who they decide to keep (or who decides to stay). This result is not very surprising and most likely stems from the restrictions on my sample, with all firms having to start with at least one college educated worker. The more surprising results come from the three rightmost columns of Table 2.9. It appears that as firms grow bigger, there is some reorganization among the workers who are left from the previous years, with the lower skilled workers disproportionately more likely to stay with the firm compared to high-skilled workers. Therefore, the decline in overall average wages comes not only from the hiring of a larger number of lower skilled workers as firms grow, but from skilled workers disproportionately leaving the firm.

Table 2.11 investigates if the reorganization of stayers discussed above occurs not only among but withing educational groups as well. It provides the results of the regression of average wages in each skill group among stayers on sizes. Yet again, we see a confirmation of a firm size-wage premium in Brazil, in this case a rather large one, with larger firms offering significantly higher wages to their previously employed workers, as stated in the three leftmost columns of Table 2.11. The three rightmost columns show that as firms expand, wages do not change significantly within the education groups. This suggest that to the extent that there is re-

Table 2.10: Log of Starting Wages by Groups

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Size	0.04***	0.06***	0.08***	-0.004	-0.01***	-0.03*
	(0.003)	(0.004)	(0.006)	(0.005)	(0.002)	(0.01)
Constant	-0.07***	0.07***	0.89***	0.06	0.24***	1.010***
	(0.02)	(0.02)	(0.04)	(0.04)	(0.07)	(0.16)
Observations	81,337	112,308	78,930	81,337	112,308	78,930
R-squared	0.34	0.54	0.41	0.78	0.86	0.80
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

organization among the previously employed workers, a lot of it happens among and not within the educational categories. It is worth noting that with this analysis alone it is impossible to say whether firms choose to keep lower skilled workers or whether high-skilled workers choose to leave bigger firms.

Finally, consider the results of the individual-level regressions for both new hires and stayers, as presented in Table 2.12. This specification allows me to control for additional confounds that would affect average wages used in the previous specifications. Looking at the cross-section regressions for both stayers and new hires, we see the there is a positive firm size - wage premium both in terms of stayers' wages and starting wages, as we would expect. The worker-level fixed effects regressions suggest that both for stayers and new hires, if we control for the workers' skill, firms pay higher wages as they expand. Just like in the case with the analysis using all of the workers, we see that the price per unit of skill increases for both new hires and previously employed workers with the increase in firm size. The decrease in average wages, then, mostly stems from the change in the composition of workers, as shown in the firm fixed effects columns of Table 2.12. For the new hires, when firms grow, the wages go down if

Table 2.11: Log of Stayers Wages by Groups

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.08***	0.09***	0.11***	0.003	-0.003	-0.01
	(0.004)	(0.01)	(0.01)	(0.003)	(0.002)	(0.01)
Constant	0.02	0.23***	1.01***	0.03	0.41***	1.14***
	(0.03)	(0.03)	(0.05)	(0.12)	(0.09)	(0.10)
Observations	110,598	138,548	117,749	110,598	138,548	117,749
R-squared	0.44	0.54	0.38	0.89	0.92	0.89
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	No	Yes	No	No	No
Firm FE	No	Yes	No	Yes	No	Yes

Notes: Includes firm age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

we do not control for worker-level fixed effects. The discrepancy in the negative coefficient for the firm fixed level regression and the positive coefficient for the worker fixed effects regression yet again indicates that it is the change of the quantity of skill demanded as firms grow, and not the price per unit of skill that the firm is willing to pay, that drives the fall in average wages as firms expand. Notice that the firms fixed effect coefficient for the stayers is not significant, except for the interaction with the high school indicator variable. This indicates that the firm retaining workers with lower skill level as it expands is a less significant driver for the overall change in the workforce composition than the firm hiring lower skilled workers as it grows.

2.6 Firm Entry Wages and Future Firm Size

In the previous sections, I have established that larger firms do pay higher wages, on average, but as firms grow, the average wages in the firm fall, mostly due to the change in the skill composition of the firm as it expands. The coexistence of a positive relationship between firm size and average wages in the cross-section of firms and a negative relationship between

Table 2.12: Mincer Regression for New Hires and Stayers

	Ind FE	New Hires Firm FE	Worker FE	Ind FE	Stayers Firm FE	Worker FE
Size	0.02***	-0.03***	0.02**	0.04***	-0.01	0.03***
	(0.01)	(0.01)	(0.01)	(0.09)	(0.01)	(0.01)
HS	0.35***	0.17***	0.31**	0.49***	0.28**	0.13***
	(0.05)	(0.03)	(0.13)	(0.06)	(0.03)	(0.03)
Coll	0.83***	0.55***	0.91***	0.95***	0.59***	0.25***
	(0.10)	(0.10)	(0.15)	(0.10)	(0.10)	(0.05)
HS × Size	-0.03***	-0.002	-0.03	-0.04***	-0.01***	-0.01*
	(0.01)	(0.003)	(0.02)	(0.01)	(0.005)	(0.004)
Coll × Size	0.03*	0.04**	-0.02	0.01	0.034***	0.001
	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
Constant	0.29	0.59***	-0.50*	0.92**	1.24***	0.22***
	(0.19)	(0.21)	(0.26)	(0.37)	(0.25)	(0.05)
Observations	16,180,273	16,180,273	16,180,273	23,274,865	23,274,865	23,274,865
R-squared	0.60	0.72	0.97	0.66	0.76	0.97
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	No	No	Yes	No	No
Industry FE	Yes	No	No	Yes	No	No
Firm FE	No	Yes	Yes	No	Yes	Yes
Worker FE	No	No	Yes	No	No	Yes

Notes: Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

firm size and average wages in the life cycle mean, mechanically, that firms that end up growing large have to start with higher wages. In this section of the chapter, I briefly address whether that is the case. To test this hypothesis, I run the following regression for the average firm quantities:

$$y_{ft} = \beta_1 \text{LogN}^0_{ft} + \beta_2 \text{LogWage}^0_{ft} + \beta_3 \text{ShareHS}^0_{ft} + \beta_4 \text{ShareColl}^0_{ft} + \alpha_r + \alpha_t + \varepsilon_{ft}$$

Superscript 0 indicates that the variables in question are the quantities at birth. So LogN^0_{ft} means the log of the size of the firm when it was formed. The outcome variable, y_{ft} in this case, is the log of size of the firm at a given age. This regression evaluates whether firms starting larger and with higher wages and proportionately more higher skilled workers end up growing into the big firms in the cross-section. So each column of Table 2.13 represents the regression

Table 2.13: Predictive Power of Size and Wages at Birth

VARIABLES	Size at 0	Size at 1	Size at 3	Size at 5	Size at 10	Size at 15	Size at 19
Entry Size		0.84***	0.71***	0.67***	0.66***	0.64***	0.53**
		(0.01)	(0.03)	(0.04)	(0.06)	(0.11)	(0.26)
Entry Wage	0.42***	0.08***	0.12***	0.09***	0.18***	0.09	-0.24
	(0.03)	(0.01)	(0.02)	(0.02)	(0.05)	(0.08)	(0.24)
Entry HS%	-0.45***	0.06**	0.09**	0.15**	0.34**	0.44**	0.06
	(0.07)	(0.03)	(0.05)	(0.06)	(0.14)	(0.22)	(0.74)
Entry Coll%	-3.11***	0.61***	0.84***	0.99***	1.17***	1.33***	1.03
	(0.12)	(0.05)	(0.07)	(0.10)	(0.18)	(0.30)	(0.76)
Constant	2.97***	0.08	0.77***	1.07***	1.17***	2.85***	4.72***
	(0.20)	(0.09)	(0.12)	(0.14)	(0.39)	(0.42)	(0.94)
Observations	26,603	22,182	15,573	10,688	4,282	1,513	301
R-squared	0.54	0.67	0.50	0.45	0.47	0.55	0.65
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01.$

described above, where the outcome variable is the size of all firms at ages 0, 1, 3, 5, 10, 15 and 19. Each columns presents a balanced panel, as all the firms need to have survived until this age to make it into the analysis.

Table 2.13 presents the result. First of all, we see that firms that start with higher wages on average tend to start with more workers. Interestingly, the negative coefficients on the share of HS workers at age 0 and share of Coll workers at age 0 mean that firms that start with more workers tend to start with more Prim workers (the omitted category here). Note that this regression is performed in the sample of high-performing firms that only start with at least one Coll worker. Firms that start large start with very few Coll workers. If the firms has a high share of Coll workers, it is most likely small compared to other firms.

Secondly, as we look at older firms by moving to the right in the table, we see that some variables are highly predictive of future size, such as size at age 0 and wages at age 0. Firms that start with higher wages have more workers than their counterparts throughout their entire life cycle. Interestingly, having proportionately more college workers at age 0 is also associated with having more workers further into the firm life cycle, even though it dampens the firm's size at age 0. This table states that it is indeed true that firms that end up being large start with higher wages, which would be consistent with the main results of the paper.

Table 2.14 presents results of a similar regression, except now instead of using average wages throughout the firm I use the average wages of workers within the education groups. The results are similar to the ones presented in Table 2.13. We see that firm size at age 0 is still highly predictive of size when firms get older. Firms that pay higher wages to all of their workers start up bigger than other firms, and a high share of Coll workers is associated with lower starting size. However, as we look at the firms at an older age, we see that of all the education groups only the variables related to Coll workers can predict the future employment. Firms that start with higher Coll wages and proportionately more Coll workers end up larger, despite the negative penalty for the employment at age 0. This seems to imply that these firms grow faster, if they are able to overcome their relatively low size at age 0 and end up larger than other firms as they age.

2.7 Conclusion

This paper examines what happens to the average wages in the firm as firms expand. I find that average wages fall as firms increase their employment, even though in the cross-section a significant firm size - wage premium persists. This is possible due to the fact that firms that end up growing large start with relatively high wages. I separate the workers into three skill groups, using educational attainment as a proxy for skill. I find that when firms expand, they shift their workforce composition towards less skilled workers both across the skill groups (by hiring disproportionately more workers with low educational attainment) and within skill groups. I also find that after controlling for worker fixed effects, firm tenure and education, firm expansion is associated with an increase in wages. A large proportion of the workforce composition adjustment comes from hiring relatively low-skilled workers, even though there is

Table 2.14: Predictive Power of Size and Wage by Group at Birth

VARIABLES	Size at 0	Size at 1	Size at 3	Size at 5	Size at 10	Size at 15	Size at 19
Entry Size		0.92***	0.84***	0.81***	0.71***	0.64***	0.56***
		(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.12)
Entry PR Wage	0.08***	-0.01	-0.01	-0.01	0.02	0.004	0.02
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)	(0.16)
Entry HS Wage	0.15***	0.0003	-0.004	-0.03	0.01	0.07	-0.28*
	(0.04)	(0.01)	(0.02)	(0.02)	(0.04)	(0.06)	(0.14)
Entry CL Wage	0.31***	0.041***	0.06***	0.062***	0.052***	0.06*	0.27***
	(0.0225)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.10)
Entry HS%	-0.07	0.072***	0.13***	0.22***	0.12*	0.09	0.27
	(0.12)	(0.03)	(0.04)	(0.05)	(0.07)	(0.13)	(0.37)
Entry Coll%	-2.42***	0.21***	0.32***	0.46***	0.40***	0.66**	1.10*
	(0.37)	(0.04)	(0.06)	(0.08)	(0.11)	(0.26)	(0.66)
Constant	2.95***	0.13**	0.36***	0.36***	0.73***	1.51***	0.81*
	(0.18)	(0.06)	(0.08)	(0.11)	(0.22)	(0.32)	(0.42)
Observations	68,246	53,089	36,709	26,171	11,989	4,382	911
R-squared	0.38	0.79	0.65	0.59	0.53	0.52	0.60
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

also evidence of internal reorganization of already employed workers, with lower skilled workers seemingly being retained more. These results need further investigation, even though they are somewhat consistent with the theory of firm reorganization presented by Caliendo et al. (2015b).

What could be the driving force for these patterns? One possible mechanism is outlined in Chapter 1 of this dissertation: firms' need to accumulate organizational capital. If we assume that high-skilled workers are important to organizational capital accumulation within the firm, then the empirical results presented in this chapter reinforce the conclusion of Chapter 1. Small firms need proportionately more high-skilled workers because they are accumulating organizational capital. The fact that the negative relationship between average wages in the firm and firm size is more pronounced for firms at the beginning of their life cycle hints towards the fact that this push towards lower skill workforce is strongest when firms are young and they need to accumulate organizational capital faster. The fact that the share of high-skilled workers at birth is highly predictive of future firm size, even though firms that start with a higher proportion of high-skilled workers tend to start smaller, lends support to the hypothesis that firms that invest heavily in organizational capital early on in their life cycle end up benefiting from this investment and outgrowing their competition. In future work, I aim to further investigate what drives firms' demand for skill and what implications it might have on the aggregate outcomes for workers, such as wage inequality and employment polarization.

Chapter 3

Corruption and Worker Competence

3.1 Introduction

Governments play a crucial role in facilitating economic development, reinforcing private property rights and addressing positive and negative externalities, and the quality of governance is intrinsically linked to the overall competence of the workforce in the public sector (see Finan et al. (2015)). Ensuring that government officials, be it on the federal or local level, are selected based on their ability and commitment is a tall order, especially in developing countries that might be dealing with higher levels of corruption. It is hence important to develop effective incentive and monitoring measures that help attract the best candidates to the public sector and ensure that the best candidates are selected.

In this paper, I study whether anti-corruption measures not explicitly targeting the allocation of public sector jobs to workers based on nepotism or political affiliation can nonetheless affect the overall competence of the public sector workforce. In the context of Brazil, which introduced a random audit program in 2003 which targets the potential misuse of federal funds by municipal governments, I examine whether once a municipality has been audited and has been revealed to engage in corrupt practices there is an effect on the overall competence level of municipal workers. Following Colonnelli et al. (2020), I use two measures of competence for workers: the residuals from the Mincer regression using the workers' wages in the private sector and whether the workers satisfy the minimum education requirements outlined in their job description.

There are three theoretical possibilities of how the revelation of corruption in the municipal government could affect the selection into who is hired and who is retained in the public sector. Firstly, the revelation of corruption could ultimately lead to an improvement in the overall competence level of the municipal workforce. Patronage plays an important role in who gets hired to work in the municipal government in Brazil, as shown by Colonnelli et al. (2020). In this case, if the incumbent administration is found to have engaged in misappropriation of federal funds, then this revelation could lead to the "purge" of the workers who might have not been employed based on their merit but based on their political affiliation to the administration or serve as a deterrence for future nepotism-guided hiring.

On the other hand, the revelation of corruption might have a negative effect on the overall competence level of municipal workers, if competent individuals do not want to associate themselves with an entity that has just gone through a scandal with high reputation costs. The outcomes of the audits are highly publicized, and the general public pays attention to the elected officials who have been revealed to engage in corrupt practices. (Weitz-Shapiro and Winters (2016); Ferraz and Finan (2008))). The effects of a reputation loss on the performance of private companies has been briefly examined in the economics literature, but has mostly been confined to the effects of reputation loss on the firms' stock market performance (Wang et al. (2015), Barko (2018)) due to data availability. An exception is the recent work of Gadgil and Sockin (2020), who use Glassdoor [1] data to examine how the loss of the firm's reputation affects rank-and-file workers in the firm and find that not only do the workers see a decrease in their total compensation, but as a result of the decrease in worker job satisfaction, companies struggle to

[1] a website where current and former employees can anonymously review companies

fill vacancies after a scandal. It is possible that more competent workers in the public sector will also shy away from the negative limelight of a municipal administration that was caught in the corrupt act, which would lead to the decrease of the overall competence level of the municipal workforce.

Finally, it is possible that the audits that investigate how federal funds are used by municipal authorities will not have any effect on the overall competence level of the municipal workforce. This can be due to the fact that the audits do not explicitly concern themselves with hiring practices or due to the fact that the public sector labor market in Brazil is notoriously rigid and heavily regulated. For example, for certain positions public sector employees get permanent tenure after three years of employment (Colonnelli et al. (2020)), and wage changes have to go through an extensive negotiation process with labor unions.

In this paper, I present tentative evidence that in municipalities that have been audited and reveled to be corrupt there is a subsequent increase in the overall competence level of public sector workers. The effect is apparent in the next four years after the revelation of corruption and begins to taper off after that. I also find no effect on the competence level on the workforce if a municipality is simply audited and not revealed to be seriously corrupt, it is the revelation of serious violations that seems to be driving the effect. I also study whether the increase in the overall level of competence is due to the improvement of hiring practices after the revelation of corruption or due to the previously employed unqualified workers leaving the public sector. I find that the results are mostly driven by the new hires, where the competence of newly hired workers after the revelation of corruption increases, whereas the average competence level of the "stayers" - the workers hired prior to the audit - does not. This presents evidence that supports Colonnelli et al. (2020)'s conclusion that patronage is an important feature of the hiring process in Brazil's municipal governments, which might temporarily become less prevalent after the municipality goes through the scandal and the publicity of revealed corruption.

This paper contributes to two strands of literature. Firstly, there is a vast body of literature that examines the effectiveness of various anti-corruption measures (e.g. Smith et al. (1984), Giannetti et al. (2020), Chen and Kung (2019), Christensen et al. (2020)) and audits in particular (see Olken (2007); Bobonis et al. (2016)). The context of random municipal audits in Brazil has proven to be particularly fruitful in illuminating the effectiveness of monitoring and auditing initiatives on reducing corruption. Starting with the seminal papers by Ferraz and Finan (2008, 2011) which looked at the effects of audits on elected officials behavior in office and their chance of being re-elected, there has been a number of papers examining the effect of the audits on various areas of the Brazilian economy. Funk and Owen (2020) find that audited municipalities see an improvement in performance and governance along a number of metrics, whereas Avis et al. (2018) find that audits reduce the likelihood of future corruption and Zamboni and Litschig (2018) find that audits deter future rent extraction by municipal authorities. Colonnelli and Prem (2019) and Prem et al. (2021) examine the firm side of the economy and find that audits and subsequent sanctions lead to higher growth for some exposed firms and increase in economic activities in sectors that depend most on government contracts. I show that another avenue of potential improvement in the performance of the Brazilian economy that can be affected by the random audits is the overall competence of the municipal personnel, and I find that municipalities that are exposed to be corrupt see an overall improvement in the competence level of the municipal workers after the audits.

Secondly, this paper contributes to the literature on selection and quality of public sector workers, reviewed in great detail in Finan et al. (2015). Numerous studies analyze which incentives are effective in improving the selection and performance of public sector workers (see Khan et al. (2014) and (2019), Fisman and Wang (2017), Deserranno (2019), Bertrand et al. (2020)) and the effectiveness of oversight on improving performance in the public sector (see Iyer and Mani (2012), Gulzar and Pasquale (2017)). In the context of Brazil, there are several studies that are of particular relevance to this work. Akhtari et al. (2017) find that political party turnover in municipal elections negatively affects education provision, which they connect to political discretion in the hiring of municipal educational bureaucracy. Brollo and Pedro Forquesato (2018), Barbosa and Ferreira (2019) and Colonnelli et al. (2020) study the role of patronage in public sector hiring using different populations of supporters of winning electoral officials. In particular, Colonnelli et al. (2020) find that patronage plays an important role in municipal government hiring, with supporters of winning mayors in close electoral races more likely to become municipal workers across a broad set of occupations. They also find that this preferential treatment of politically connected individuals negatively affects the overall competence level of the municipal workforce in Brazil. I find evidence that audits and revelation of serious corruption acts leads to the overall improvement of the general competence of municipal workers in audited municipalities, with the difference stemming from the new hires before and after the audits. One possible explanation for this effect is that the negative attention associated with exposed corruption discourages patronage-driven hires, which temporarily leads to more merit-driven hiring.

The rest of the paper is organized as follows. Section 2 presents a very brief overview of the audit program and the labor market institutions in Brazil, Section 3 describes the statistics and the data used to measure competence and corruption, Section 4 describes the empirical strategy, Section 5 presents the results and Section 6 concludes.

3.2 Institutional Background

The Audit Program

The municipal audits program started in 2003 and was aimed at investigating any potential misuse of federal funds by municipal governments. Only municipalities below a certain population threshold were eligible to be audited, with the population threshold set at 100,000 in 2003 and increasing to 500,000 by the end of the audit program. As of 2014, 1,881 municipalities were audited at least once out of the 5,570 municipalities in Brazil. The selection of municipalities for audit each year was done through a lottery, with 39 lottery rounds in total, and each draw was open to the press, politicians and the general public. After the lottery, the audit process starts immediately and usually lasts around 10 days. A team of competitively selected auditors physically travel to the municipalities and manually review all of the documentation regarding the use of federal funds and actually inspect any projects that are funded with federal transfers. They then compile their findings in a report which eventually becomes publicly available in which they note any irregularities in the use of federal funds together with any justifications provided by the municipal authorities. The audits report the names of the public officials that are implicated in corrupt activities, such as fraud, over-invoicing or the diversion of funds. The outcomes of the audits are publicized, citizens pay attention to them and vote accordingly if their municipality is revealed to be corrupt (see Weitz-Shapiro and Winters (2016) and Ferraz and Finan (2008)). In addition, the federal government may choose to proceed with fines or other legal sanctions against individuals who were found to engage in corrupt practices.

The Labor Market in Brazil

The labor market in Brazil is notoriously rigid and regulated. Campos and Nugent (2012) create an index of labor market rigidity using data on 140 countries since 1960 and place Brazil in top 10% countries with most rigid labor markets. For example, Brazilian labor law does not allow changing one worker's wages without adjusting the wages of all the other workers in the same firm (Engbom and Moser (2018)). Public sector employment is also subject to numerous regulations. Most employees have to go through an official screening process and pass a job-specific formal civil service exam (*Concurso Publico*) in order to be hired. If they are hired through this process and remain employed for three years, they obtain tenure, at which point they can only be fired in case of misconduct or by a judicial ruling. Colonnelli et al. (2020) find that around 70% of all public sector jobs are allocated through the *Concurso Publico* process, which means that the majority of public workers enjoy a high degree of job security.

3.3 Data and Measures of Corruption and Competence

In this paper, I rely on two main data sources. The first one is the *Relação Anual de Informações Sociais* (RAIS) dataset, which I described in a lot of detail in the previous two chapters of this dissertation. Importantly for this chapter, each individual in RAIS gets assigned their employer's legal status, which allows me to examine all of the workers in the municipal executive branch in the audited municipalities in my sample. I focus on years 2000-2014 which gives me data on the characteristics on of the municipal workers 5 years before the earliest audits in my data and 6 years after the latest audits. I also have access to the entire work history of the municipal workers, which allows me to obtain the Mincer residuals that I use as the main measure of worker competence in this chapter.

Like Dal Bó et al. (2013) and Colonnelli et al. (2020), I focus on the outside options available to the municipal worker for my main measure of competence. For each worker in each year, I identify the highest paying job in the private sector [2] and run a Mincer earnings regression controlling for a full set of interactions between the worker's age, education entertainment, and employment sector, as well as for municipality fixed effects. The residuals from this regression represent a measure of the worker's innate ability, which I use as the overall measure of competence for the worker.

The second measure of competence is based on the worker's education and the education requirement of the job that they occupy in the municipality. I use the list of education requirements for each job in the municipal government in Brazil presented in Colonnelli et al. (2020). I look at how the proportion of workers who are technically under-qualified for their position changes after the municipality has been audited and after it has been revealed to be corrupt. Table 3.1 presents summary statistics for the municipal workers. The majority are male and only 25% hold a college degree, even though this proportion is high relative to workers in the private sector. There is a relatively high proportion (51%) of worker-job pairs at which the worker is

[2] Only 40% of all the public sector workers in my sample have had at least one private sector job.

technically under-qualified for the job.

Table 3.1: Summary Statistics: Municipal Workers

	Mean	Median	SD
Age	40	39	10.9
Maximum Tenure (in months)	83	39	98
Mincer Residual	-0.09	-0.05	4.4
Proportion Male	0.60		
Proportion of High School Degree Holders	0.43		
Proportion of College Degree Holders	0.25		
Proportion of Under-qualified Workers	0.51		
N of Unique Workers	945,225		
N of Observations	5,603,665		

For the measure of corruption, I rely on the *narrow* definition of corruption introduced in Brollo et al. (2013) and the dataset of corruption measures that they compiled from the actual audit reports published online. The audits report information that can be interpreted as evidence of corrupt practices or simply of poor management of funds and inexperienced administration. To focus on the most visible offenses that are most likely to either deter the competent workers form seeking employment in the public sector or to deter the administration from using municipal government jobs as a reward for their political supporters, I only consider a municipality corrupt when the report includes severe irregularities such as fraud, over-invoicing, favoritism or severe illegal procurement practices, such as manipulating the bid in the procurement process. In the analysis presented below, I use a binary variable that takes the value of one if any instances of severe violations were detected. Due to data availability, I only consider the municipalities audited in 2005-2008, in lottery rounds 19 and 21-27. This leaves me with 480 municipalities, for 65% of which the audits report at least one severe act of corruption.

3.4 Empirical Strategy

I estimate the static and dynamic effects of a municipality being revealed as corrupt on the overall competence level of municipal workers. The main regression specification is run on the sample of municipal workers in audited municipalities and takes the following form:

$$y_{it} = \beta \times Corrupt + \alpha_{year} + \alpha_{muni} + const + \varepsilon_{it} \tag{3.1}$$

with standard errors clustered at the municipal level. *Corrupt* is an indicator variable that takes the value of 1 in the years after the audit only if the audit revealed serious acts of corruption in the municipality. y_{it} here represents either the Mincer residual for each worker described in the previous section or an indicator variable that takes the value of 1 if the worker's educational attainment is below the level that is officially required for their job. The identification relies on the timings of random audits, where the main comparison is between municipalities that are yet to be audited, at which point some of them will be exposed as corrupt, and municipalities that have already been audited and have been revealed to be corrupt.

I also run the following regression to identify the timing of the effects of the disclosure of corrupt practices:

$$y_{it} = \sum_{s=-2}^{+5} \beta_s \times Corrupt_m \mathbb{1}(s=t) + \alpha_{year} + \alpha_{muni} + const + \varepsilon_{it} \tag{3.2}$$

The coefficients of interest in this regression are the β_s which disclose how the overall competence level of the municipal workforce changes at most two years before the revelation of corruption and up to 5+ years after the audit.

In addition to examining how the revealed corruption affects the competence of the workforce, I also perform the two regressions described above with *Audit* as the independent variable, where *Audit* is an indicator variable that takes the value of one in all time period during and after the municipality was audited, as opposed to *Corrupt* which takes the value of 1 in the year that

Table 3.2: Worker Competence & Corruption

	(1) Corrupt	(2) Audit	(3) Corrupt	(4) Audit
Effect on Mincer Residuals	0.057**	.0052		
	(.02)	(0.018)		
Effect on the share of "Under-qualified" Workers			-0.003	-0.01
			(0.12)	(0.02)
Constant	-0.14***	-.14***	1.01***	1.01***
	(0.02)	(0.02)	(0.008)	(0.008)
Observations	1,706,944	1,706,944	5,602,682	5,602,682
R-squared	0.03	0.03	0.23	0.23
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Notes: Standard Errors clustered at the municipal level.
$*p < .10, **p < .05, ***p < .01$.

the municipality was audited and after that **only if** serious violations have been detected and revealed. This allows me to ascertain whether it was the monitoring pressure of the audit or the exposure of the corrupt practices and subsequent change in hiring practices that drives the results.

3.5 Results

Table 3.2 shows the results of the estimation of equation 3.1 four times, with different dependent and independent variables. Columns (1) and (3) use *Corrupt* as the independent variable and columns (2) and (4) use *Audit* as the independent variable. In addition, columns (1) and (2) look at Mincer residuals as the measure of competence whereas columns (3) and (4) look at the probability that the employed municipal worker is "under-qualified" for their job.

In Column (1) we see that there is a statistically significant increase in the average Mincer residual in the municipalities that were revealed to be corrupt after the audit. The statistically

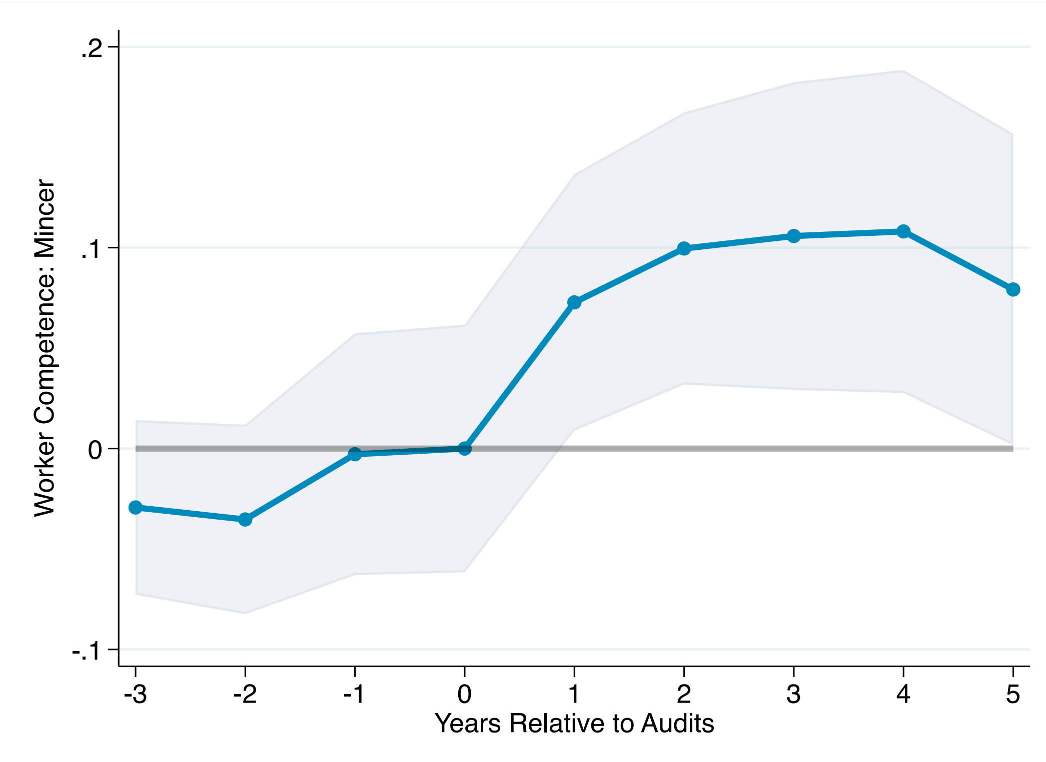


Figure 3.1: Dynamic effect of revelation of corruption on workforce competence: Mincer residuals as measure of competence

significant positive relationship is only present in the cases when municipalities were found corrupt as opposed to all of the municipalities after the audit. The results hint at the fact that it is not the scrutiny of the audit per se that generates the improvement in the overall competence of the municipal workforce, but rather the revelation of misuse of federal funds and the sanctions and changes in the aftermath. Columns (3) and (4) do not show a statistically significant relationship.

Figure 3.1 presents coefficients β_s from regression 3.2, with the year of audit coefficient normalized to 0. We can see that there is no significant effect of future revelation of corruption, which is reassuring. We can also see that the positive effect persists for a number of years after the exposure of the municipality's corruption and starts to taper off after 5 years after the audit. Using the second measure of competence, the proportion of "under-qualified" workers, Figure 3.2 shows no significant effect of a municipality being revealed as corrupt, even though the coefficients are of the right sign: there is a decrease in the proportion of municipal workers

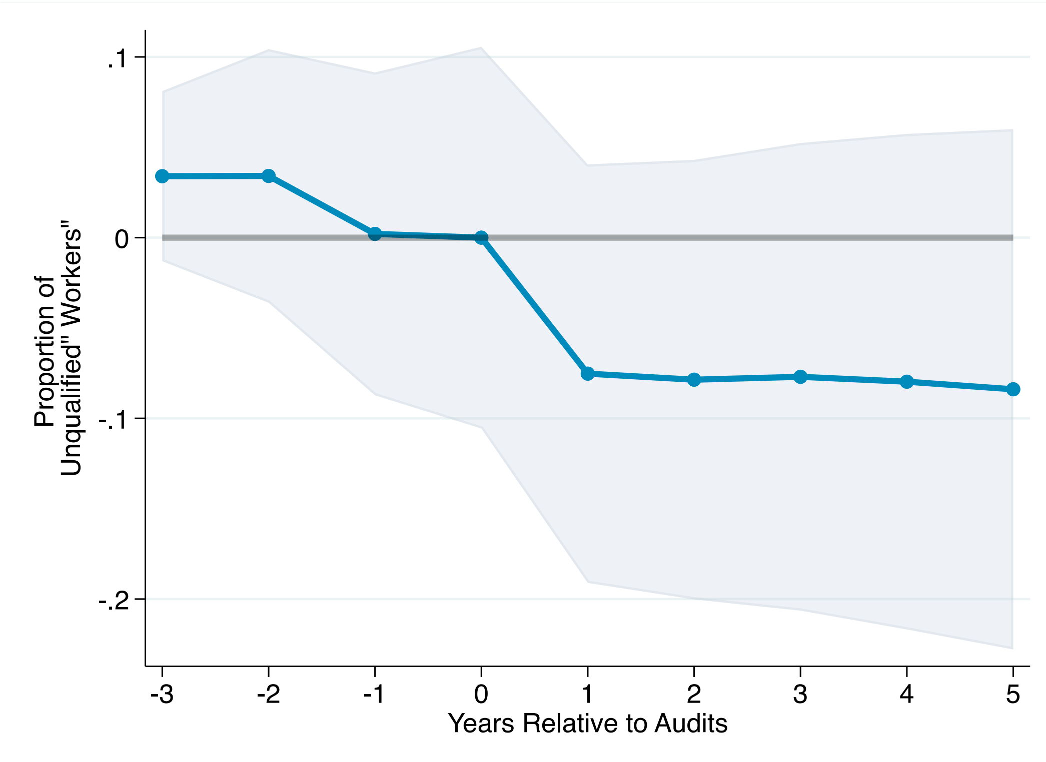


Figure 3.2: Dynamic effect of revelation of corruption on workforce competence: Probability of being under-qualified as measure of competence

whose educational attainment does not meet the formal job requirements after the audit and the exposure of corruption.

It is interesting to see whether the increase in the overall competence level of the municipal workers is driven by the change in who is hired after the municipality is revealed to be corrupt or in the change of who stays employed after the audit and the subsequent exposure of corruption. Given that the only statistically significant results are present when using the Mincer residuals as the measure of skill, I focus on those in the subsequent analysis. I estimate equations 3.1 and 3.2 on two subsamples of my data. Firstly, I look only at newly hired workers each year. Secondly, I restrict my attention only to the workers who started their employment before the audit. If there is a significant effect of the revelation of corruption in both samples, then the change in the overall competence level of the municipal workers is driven by the change in who is hired and the composition of the workers who remains employed.

Table 3.3: New Hires VS Stayers & Corruption

	(1) New Hires	(2) Pre-Audit Stayers
Corrupt	0.067**	0.02
	(.03)	(0.02)
Constant	-0.08***	-0.14***
	(0.03)	(0.02)
Observations	372,366	1,000,864
R-squared	0.05	0.04
Year FE	Yes	Yes
Region FE	Yes	Yes

Notes: Standard Errors clustered at the municipal level.
$*p < .10, **p < .05, ***p < .01$.

Table 3.3 presents the results, with column (1) showing the coefficient for new hires and column (2) showing the coefficient for workers hired before the audit. We can see that the results seem to be driven mostly by new hires, where there is a statistically significant positive effect of the municipality being audited and exposed as corrupt. The coefficient for new hires is larger than in the full specification, whereas in the case of pre-audit hires there is no statistically significant relationship and the coefficient is smaller in magnitude. One possible explanation for this result is that the highly protected nature of public sector employment prevents firing of incompetent workers that were hired before the municipality was audited, but the revelation of corruption deters future administration from using employment opportunities in the municipal government as a potential reward for their supporters and incentivizes them to at least temporarily assign the positions based more on merit rather than political connections.

Figure 3.3 shows the effect of revealed corruption on the average competence level of new hires decomposed across time. Again, we see that there is no significant effect before the audit, which suggests that municipalities most likely did not know about the fact that they will be audited in advance. We also see a positive effect that spikes straight after the audit and then

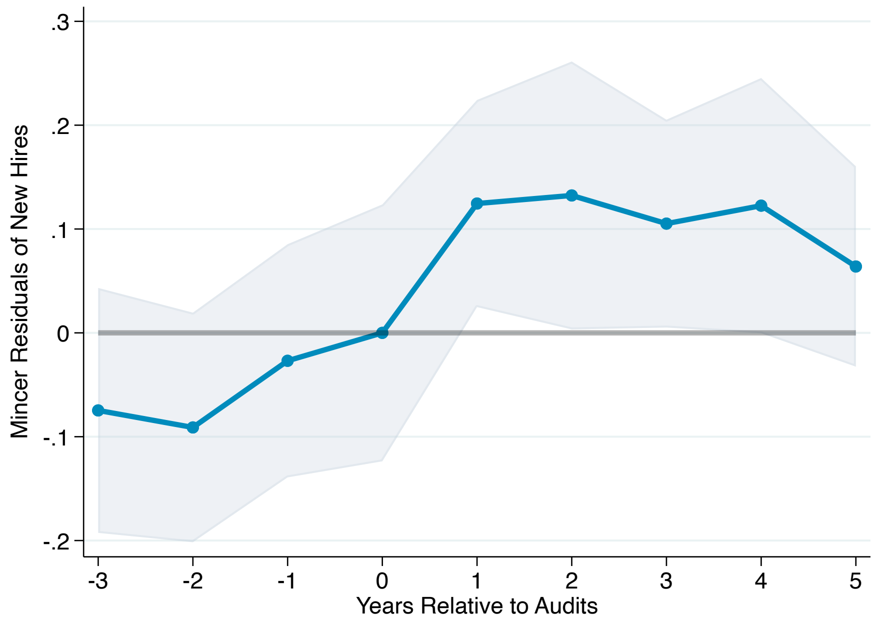


Figure 3.3: Dynamic effect of revelation of corruption on workforce competence of Newly Hired workers: Mincer residuals as a measure of competence

begins tapering off almost immediately. These results again suggest that when a municipality is audited and exposed as corrupt, the future administration is potentially deterred from using municipal employment as a patronage tool, which leads to employment opportunities in the municipal government being awarded to more competent individuals.

3.6 Conclusion

This paper presents tentative evidence that in the context of Brazil municipal audits lead to the increase in the overall competence level of the municipal workforce in the municipalities that were found to be corrupt. The results are mainly driven by the increase in the quality of new hires as opposed to the change in the composition of workers hired before the audits. One possible explanation for this phenomenon is that the revelation of corruption and subsequent sanctions temporarily deter using municipal positions as a reward for political supporters, which makes the hiring process more merit-based. In future research, I plan to examine if there is any heterogeneity across occupations and to extend the analysis to the full sample of eligible municipalities.

Appendix A

Appendix for Chapter 1

A.1 Model Extension with Stochastic Shocks

In this section, I present the version of the model of endogenous organizational capital accumulation with stochastic evolution of firm-level productivity.

A.1.1 Production Function

I introduce a new factor of production in the production function: organizational capital, Z. Z represents organizational capital and is modeled as intangible capital that cannot be purchased in the market but can instead be accumulated by skilled labor specifically designated to this task. I consider a single industry, so subscript i indicates a firm specific value and subscript t for time is omitted for simplicity unless needed. The firm specific production function takes the following form:

$$Y_i = \tilde{A}_i Z_i^{\alpha} {S_{p_i}}^{\mu} U_i^{1-\alpha-\mu} \tag{A.1}$$

U_i represents unskilled labor and S_{p_i} represents skilled labor used in the production of the good. For calibration simplicity, this production function does not include physical capital, however, including it is a simple extension. Firms are heterogeneous in their level of productivity, A, and the level of organizational capital that they have accumulated, Z. In order to accumulate organizational capital, the firm needs to dedicate some skilled workers to the task of investing into new organizational capital, so the firm decides how the skilled workers separate their time between working on production related tasks and organizational capital related task. The decision to invest into organizational capital is made today and the value or organizational capital today is fully determined by the decisions made in the previous period. The law of motion for organizational capital is as follows:

$$Z(t+1) = (1-\delta)Z(t) + S_{oi}(t)^{\theta} \tag{A.2}$$

with $0 < \theta < 1$, so the model assumes diminishing returns to investing in to organizational capital. The assumption stems from the intuition that for any given level of organizational capital at some point adding more skilled labor to come up with a blue print, a standard code for production process or a business plan is no longer as productive as adding the first unit of skilled labor to this task. I assume that organizational capital depreciates at some non-zero rate $0 < \delta < 1$. This assumption formalizes the idea that even though at one point the firm may have developed a way of doing business and compiling physical and human capital in the most efficient way that is optimal for its current market condition, a change in market conditions or customers' taste may render the previous optimal outcome obsolete and require additional investment into organizational capital.

A.1.2 Demand

As in this paper I am interested in firm growth, I do not explicitly model the household side of the economy. Demand for the firm's good is assumed to derive from the final good sector, which uses a CES aggregator across individual inputs:

$$Y = N^{\frac{1}{1-\rho}} (\sum_{i=1}^{N} Y_i^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}} \tag{A.3}$$

where $\rho > 1$ is the elasticity of substitution, N is the number of establishments in the industry and $N^{\frac{1}{1-\rho}}$ is the adjustment factor to make the degree of substitution scale free. Applying the first order conditions gives each establishment an inverse demand curve with elasticity ρ where the industry price is normalized to be $P = 1$

$$P_i = (\frac{Y}{N})^{\frac{1}{\rho}} Y_i^{-\frac{1}{\rho}} = BY_i^{-\frac{1}{\rho}}$$

where B represents the demand shifter that will later be used for the numerical estimation of the model. The production and the demand function give rise to the establishment's revenue function:

$$P_i Y_i = A_i Z_i^a S_{p_i}{}^b U_i^c \tag{A.4}$$

where I define $A_i = \tilde{A}_i^{1-1/\rho}$, $a = \alpha(1-1/\rho)$, $b = \mu(1-1/\rho)$ and $c = (1-\alpha-\mu)(1-1/\rho)$ for simplicity. Establishments have to hire skilled labor for production and organizational capital investment at the sport market wage w_s and unskilled labor at the spot market wage w_u. The wages are for skilled and unskilled wages are such that $w_{ut} = W_u(N_u)$ $w_{st} = W_s(N_s)$ where N_u and N_s are aggregate labor demand for unskilled and skilled labor respectively. Establishments also pay a fixed operational cost F each period that they choose to remain open. This defines the following profit function:

$$\Pi_i = A_i Z_i^a S_{p_i}{}^b U_i^c - w_s(S_{p_i} + S_{oi}) - w_u(U_i) - C_f$$

Given the assumptions on skilled and unskilled labor used in production, I can define the optimal choice of S_{pi} and U_p by $\frac{\partial PY(A,Z,S_p^*,U)}{\partial S_p} = w_s$ and $\frac{\partial PY(A,Z,S_p,U^*)}{\partial U} = w_u$. After imposing the skilled and unskilled labor optimality condition, I obtain the following revenue function for the establishment:

$$Y^*(A,Z) = A^* Z_i^{\frac{a}{1-c-b}}$$

where $A^* = (1-b-c)(\frac{w_u}{c})^{\frac{c}{b+c-1}}(\frac{w_s}{b})^{\frac{b}{b+c-1}} A^{\frac{1}{1-c-b}}$.

Following (), $ln(A)$ is assumed to follow an AR(1) process, so that

$$ln(A_{it}) = lnA_0 + \rho_A ln(A_{i,t-1}) + \sigma_A \varepsilon_{i,t}$$

where $\varepsilon_{i,t} \sim N(0,1)$. The productivity evolution process is independent across establishments.

A.1.3 Incumbents and New Entrants

In this model, time is discrete and all agents face an infinite horizon. There are two types of agents: incumbent establishments and potential new entrants. Each incumbent makes a choice whether to remain active or to exit. They face the following problem (dropping the i subscript for clarity):

$$V(A_t, Z_t) = \max[V^c(A_t, Z_t), 0]$$

where the continuation value is defined as follows:

$$\begin{aligned} V^c(A_t, Z_t) = \max_{S_{ot}, Z_{t+1}} & [A_t^* Z_t^{\frac{a}{1-c-b}} - w_s S_{ot} - C_f + \beta \mathbb{E}_t V(A_{t+1}, Z_{t+1})] \\ \text{s.t.} \quad & Z' = (1-\delta)Z + S_o^\theta \\ & ln(A'_{t+1}) = lnA_0 + \rho_A ln(A_{i,t}) + \sigma_A \varepsilon_{i,t+1}, \quad \varepsilon_{i,t} \sim N(0,1) \end{aligned}$$

The incumbent can choose to exit before producing anything this period if the expected value of staying operational is below 0, or they choose to stay operation and choose optimal organizational capital for the next period by choosing how much skilled labor to hire for organizational capital investment. Establishments will choose to exit if they observe a low productivity draw and do not have enough organizational capital to see them through the bad times.

There is free entry and a continuum of potential entrants that can enter with a realization of starting productivity A_0 and level of organizational capital Z_0 from a known joint distribution $G(A_0, Z_0)$. The idea behind this assumption is that there is a difference between the idea that the firm has about its product when it enters - one way to represent A_0 and the experience of the entrepreneur in starting a firm and accumulating organizational capital. They do not observe the realization of A_0 and Z_0 before entering and have to pay a one-time entry cost C_e. In equilibrium, the zero profit condition holds, so new establishments will enter until the expected value of entry is equal to the cost of starting a business. Hence, in equilibrium there will be a mass of new entrants M_e such that entry occurs until the point that

$$C_e = \int V(A_0, Z_0) dG(A_0, Z_0) \tag{A.5}$$

The distribution of $\log A_0$ is assumed normal, while Z_0 is assumed to be drawn from a uniform distribution.

A.1.4 Recursive Equilibrium

The incumbent and entrant's problems outlined above generate a joint distribution of A and Z for all firms that are active in the economy at any given period, with $F(A, Z)$ being the cumulative joint distribution of all "active" A and Z in the economy. Let $\Gamma(A_{t+1} \mid A_t)$ be the conditional CDF of A_{t+1} given A_t. It is then possible to describe a law of motion for the establishment distribution in the economy:

$$F_{t+1}(A_{t+1}, Z_{t+1}) = \int \int_I d\Gamma(A_{t+1} \mid A_t) dF_t(A_t, Z_t) + M_e \int^{A_{t+1}} \int^{Z_{t+1}} g_t(A_0, Z_0) dA_0 dZ_0 \tag{A.6}$$

where

$$I = \{(A_t, Z_t) \quad \text{s.t.} \quad V^c(A_t, Z_t) \geq \ 0, \quad Z_t(1-\delta) + S_{ot}^{\ \theta}(A_t, Z_t) \leq Z_{t+1}\}$$

The recursive equilibrium can then be defined as follows. Let the distribution of operating establishments over the two dimensions of heterogeneity be denoted by $F_t(A,Z)$ and let Θ_t denote the vector of aggregate state variables. For a given Θ_0, a recursive equilibrium consists of: *i* Value function $V(A,Z)$, *ii* policy functions $Z'(A,Z)$ and $S_o(A,Z)$, *iii*prices w_s and w_u and *iv* distribution of operating establishments $\{F(A,Z)\}_{t=0}^{\infty}$ such that given the prices w_{ut} and w_{st}

1. $V(A,Z)$, $Z'(A,Z)$ and $S_o(A,Z)$ solve the incumbents' and the entrants' problem

2. Labor markets clear

For the numerical solution of the model, I will focus on a stationary recursive equilibrium where $F_{t+1}(A,Z) = F_t(A,Z)$.

In this model, differently from Hopenhayn (1992), where firms exit when hit with a low enough productivity draw, for any productivity shock there exists a value of organizational capital where firms will not decide to exit, as the high amount of organizational capital in their possession allows them to "weather the storm" of a negative productivity shock. This approximates a situation where even if a firm is hit with a bad demand shock, for example, a high among of organizational capital, be it business systems, standards or corporate culture, allows the firm to stay afloat longer and maybe outlive the bad times.

A.2 Additional Tables

Table A.1: Most Frequent occupations by Education Group

	Prim		HS		Coll	
Rank	Occupation	%	Occupation	%	Occupation	%
1	Miscellaneous unskilled workers	5.31	Wholesale and retail sellers and related workers	5.85	Administrative agents	6.08
2	Agricultural workers	4.10	Office assistants and related workers	5.65	Office assistants and related workers	5.34
3	Office assistants and related workers	3.32	Accounting assistants, cashiers and related workers	5.33	Administrators	3.39
4	Civil construction and similar workers	3.22	Administrative agents	5.14	Administrative workers (general)	3.24
5	Field-crop growers	2.86	Telephone, telegraph and related communications operators	3.77	Systems analysts	3.15
6	Car, bus, truck and similar vehicle drivers	2.24	Telephone, telegraph and related communications technician	3.63	Administrative and similar managers	2.71
7	Cooks and meal packers	2.17	Other unskilled workers n.e.c.	3.45	Administrative and similar managers (senior)	2.45
8	Maintenance and cleaning workers	2.16	Stock keeping and conveyance operators	2.08	Wholesale and retail sellers and related workers	2.00
9	Fruit growers and plantation workers	1.91	Stock Manager	1.20	Financial and commercial managers	1.94
10	Specialized agricultural growers and workers	1.91	Security guards	1.17	Pharmacists	1.69
T		30%		39%		35%

A.3 Computational Stationarity

In this section, I present computational evidence that the model arrives at a stationary firm distribution. Stationary equilibrium requires that the distribution of organizational capital Z_i and firm-level technology A_i that are "active" in the economy remain constant across time. As shown in Hopenhayn (1992), this leads to the firm size distribution being constant across time, which allows me to abstract away from the potential changes in equilibrium wages across time and firms having to form expectations about future wages when they make decisions about organizational capital investment today. c Below, I present plots from the simulation of the model across 2000 years, with the last 1000 years depicted in the diagram. I plot the deviation of the overall size of the resulting workforce in the economy from the mean across all time periods, as well as the deviation of the total skilled and unskilled labor force from their respective means. I also present a plot of the overall number of active firms in the economy, as well as the number of entrants and firms that exit the market. We can see that the deviation away from the mean is within 1% (represented by the red lines in the graphs) for the size variables and the number of active firms, as can bee seen in Figures A.1 and A.2.

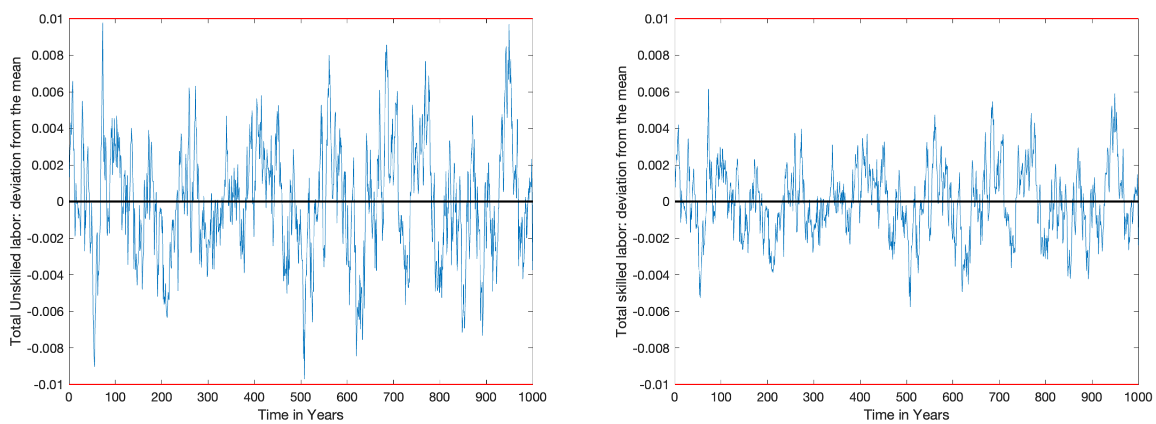


Figure A.1: Both graphs show percentage deviations form the mean. Left: Deviation of total yearly unskilled employment; Right: Deviation of total yearly unskilled employment.

We can also see in Figure A.3 that the number of entrants and exiting firms remains

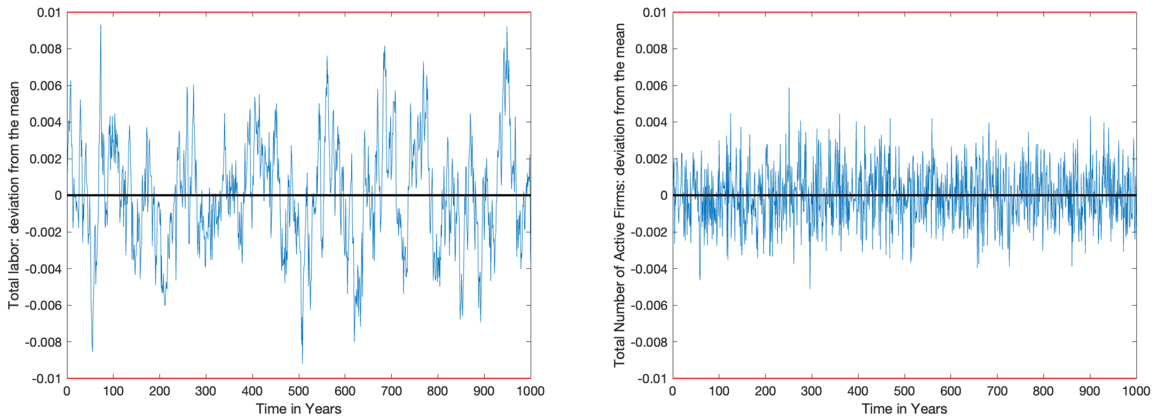


Figure A.2: Both graphs show percentage deviations form the mean. Left: total yearly employment in the economy; Right: total number of firms that are active in the market each year.

roughly constant across time, although it does fluctuate more than the size of the labor force in the economy (the purple lines indicate a +/- 3% deviation). The average number of entrants is equal to the average number of exiting firms, at on average 12,287 entries and exits occurring each year (out of 85,000 firms). We can conclude that the equilibrium discussed in the main body of the chapter is computationally stationary.

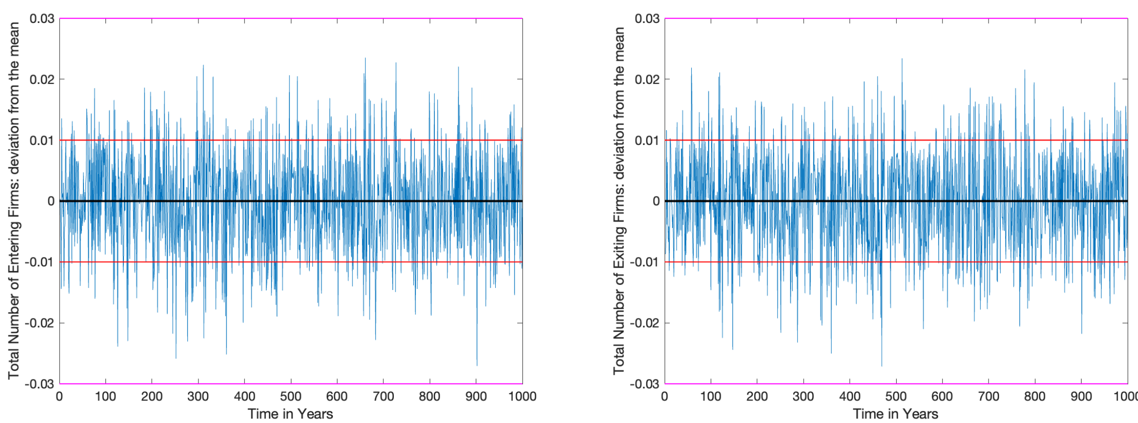


Figure A.3: Both graphs show percentage deviations form the mean. Left: The number of entrants; Right: the number of exiting firms.

A.4 Robustness checks: Empirical Results for the different specification of the worker-level FE

In this section, I present the results pertaining to the evolution of average skill in the firm with size and age, where average skill is measured as the worker-level fixed effects from the following regression:

$$\text{LogWage}_{wt} = i.\text{Years of Education}_w\#\#(\text{year}_t, \text{age}_w^2, \text{age}_w^3) + \alpha_w + \varepsilon_{pt} \tag{A.7}$$

where the years of schooling are fully interacted with calendar year and age squared and cubed for a measure of experience. The worker-level fixed effects are then extracted and standardized, where each workers gets assigned a personal measure of skill which is the deviation of their fixed effect from the mean. In this case, the measure of skill represents the innate ability of the worker, as the effects of experience and education are netted out.

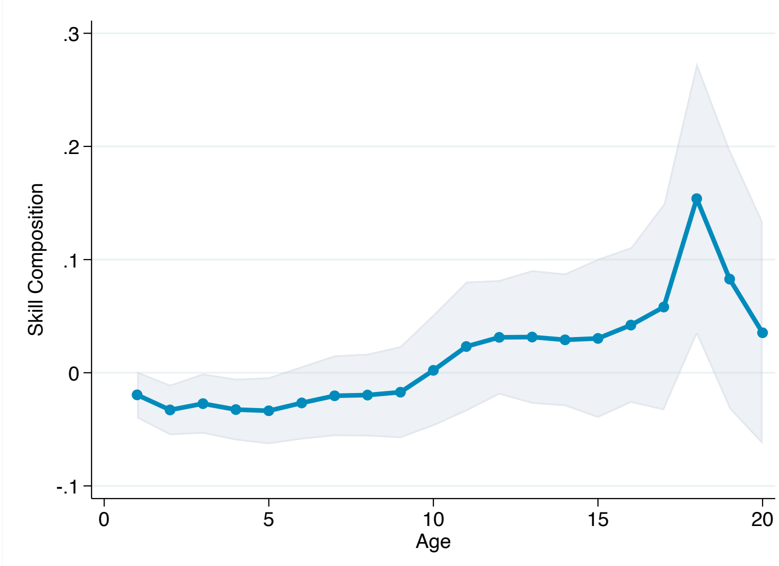
The overall results using this slightly modified measure of skill are very close qualitatively and quantitatively to the main results in Chapter 1.

Table A.2: Average skill as Alternative Worker FE and Size

	Industry FE	Firm FE
Log of Size	0.011	-0.072***
	(0.009)	(0.008)
Constant	1.031**	1.043***
	(0.415)	(0.107)
Observations	149,845	149,845
R-squared	0.178	0.805
Year FE	Yes	Yes
Region FE	Yes	No
Industry FE	Yes	No
Est FE	No	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

A



B

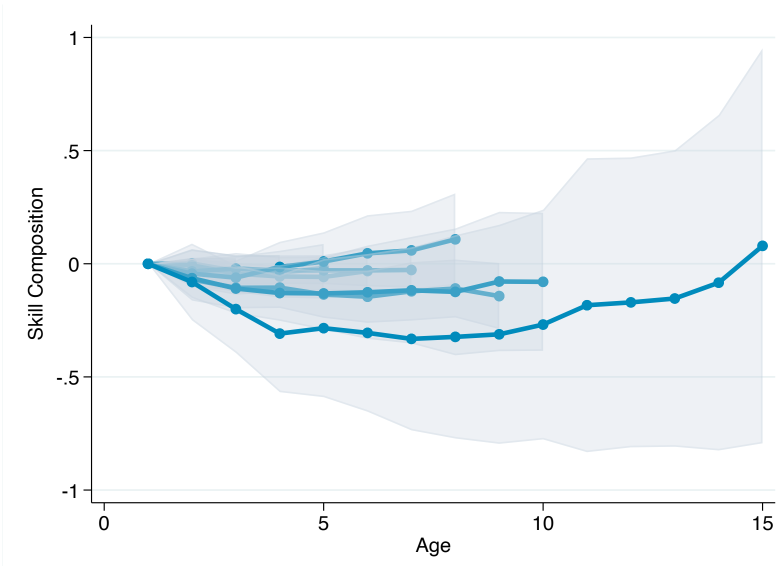
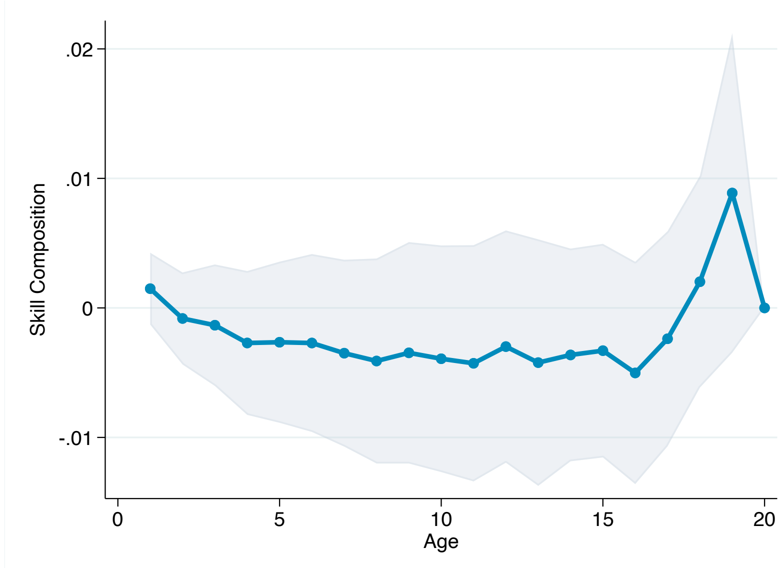


Figure A.4: Firm Skill Composition and Age in the Cross-Section: Unbalanced Panel and Firms by Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. Panel A shows the result of the regression in an unbalanced panel of firms. Panel B shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

A



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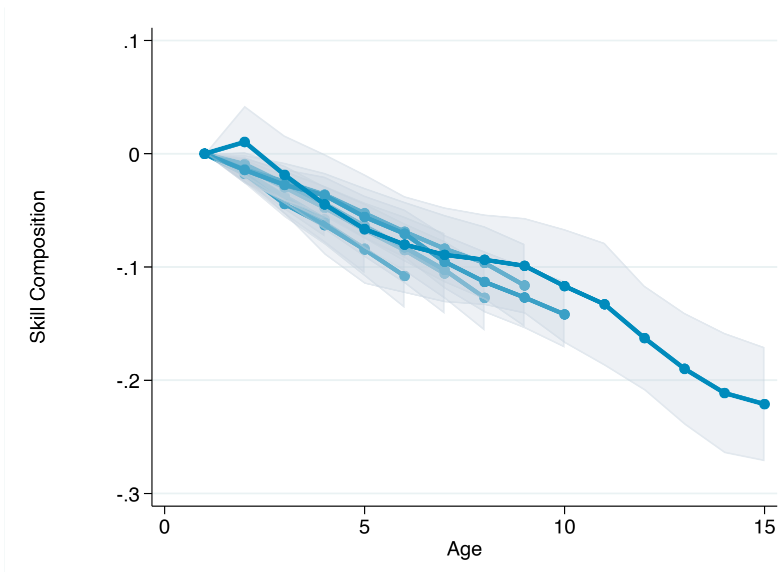

Figure A.5: Firm Skill Composition and Age in the Life Cycle: Unbalanced Panel and Firms by Survival Age

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. Panel A shows the result of the regression in an unbalanced panel of firms. Panel B shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

A.5 Robustness checks: Results for Different Samples

A.5.1 Empirical Results for the full sample of firms

In Chapter 1, I looked at a subsample of firms, namely the firms that employ college educated workers from the onset. The subsample of firms represents what I call "successful" firms which are conceptually more likely to be gaining a lot from organizational capital investment. Below, I replicate the empirical results presented in Chapter 1 in the full sample of firms as a robustness check.

Most of the results qualitatively carry through in the full sample of firms: as firms grow, the average level of skill of their workforce declines, regardless of the measure of skill used. The same can be said about the relationship between average firm-level skill and age, with one notable exception: in this sample, the share of college educated workers increases with age in a balanced panel, as can be seen in Figure A.7. However, using the more sophisticated measure of skill, the results presented in Figure A.9 are consistent with the findings presented in the main body of Chapter 1.

Table A.3: Worker Composition and Size: Full Firm Sample

	Skill as Share of Coll		Skill as Worker FE	
	Cross-Section	Life Cycle	cross-section	Life Cycle
Log of Size	0.002	-0.005***	0.028***	-0.012***
	(0.001)	(0.001)	(0.004)	(0.002)
Constant	0.027***	0.03***	0.134	0.181***
	(0.011)	(0.0053)	(0.083)	(0.013)
Observations	1,412,267	1,412,267	1,360,163	1,360,163
R-squared	0.205	0.628	0.20	0.77
Year, Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	No	Yes	Yes

Notes: Includes age fixed effects. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

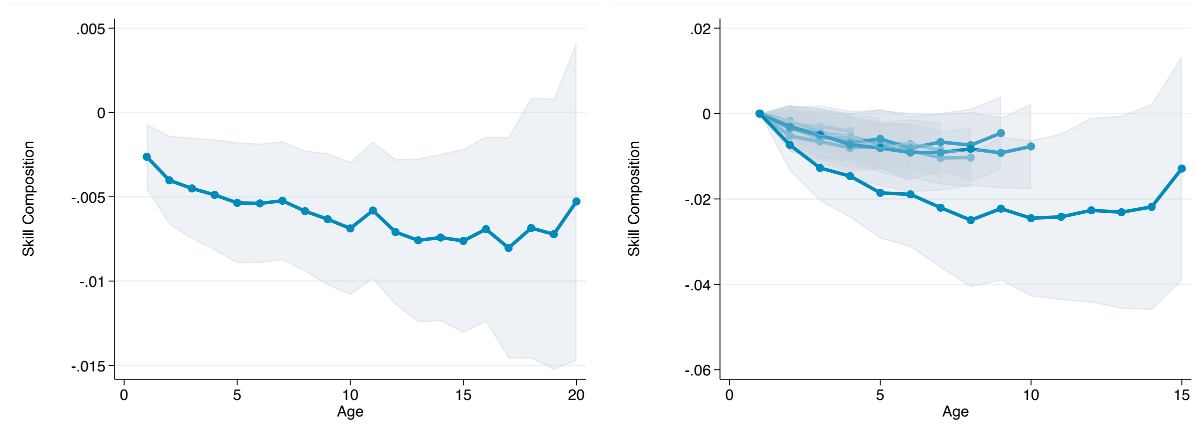

Figure A.6: Skill as Share Coll & Age in the cross-section Regression: Full Firm Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

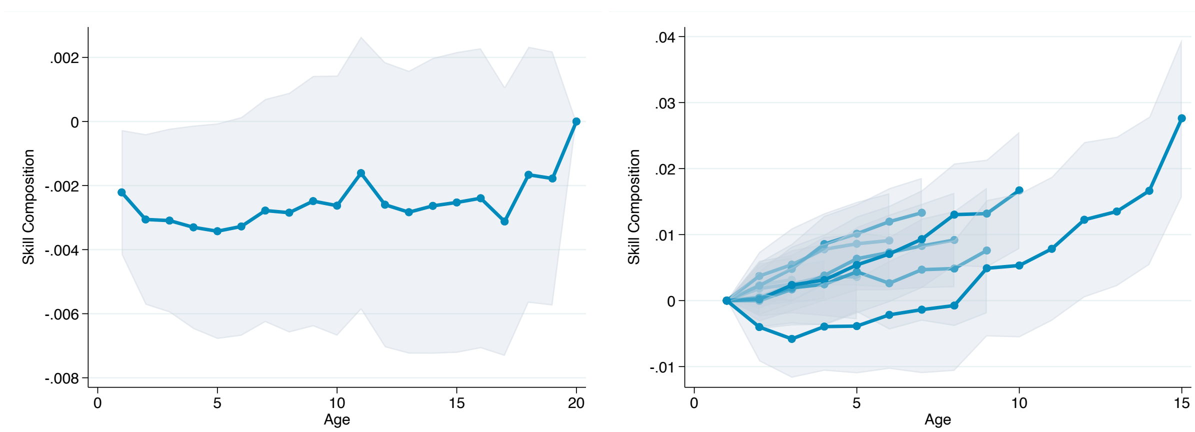

Figure A.7: Skill as Share Coll & Age in the Life Cycle Regression: Full Firm Sample.

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

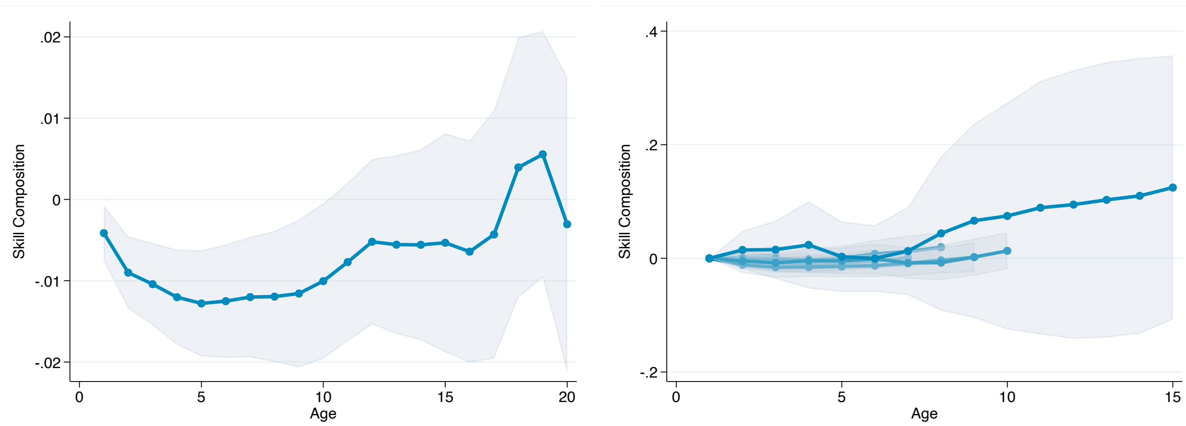

Figure A.8: Skill as Worker FE & Age in the cross-section Regression: Full Firm Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

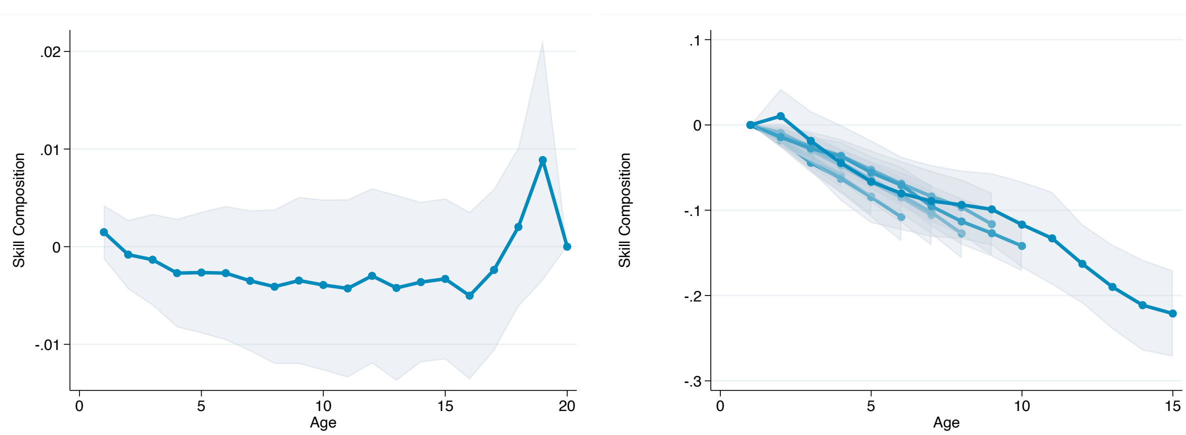

Figure A.9: Skill as Worker FE & Age in the Life Cycle Regression: Full Firm Sample.

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

A.5.2 Empirical Results for the Sample of Establishments Born with Coll workers

In the main body of Chapter 1, I consider firm-level evidence. Below, I replicate the empirical results presented in the main body of Chapter 1 using *establishment* rather than firm-level evidence. An establishment is an economic unit that produces goods and services, usually at a single physical location. Firms can consist of one or more establishments. In the main body of Chapter 1, I argue that hiring and organizational capital investment decisions are more likely to be made at the firm rather than establishment level. As a robustness check, I present the empirical results of the regressions outlined in the main body of Chapter 1 estimated on a sample of establishments that start off with some college educated workers. All of the results are qualitatively similar to the main results.

Table A.4: Worker Composition and Size: Establishments Born with Coll

	Skill as Share of Coll		Skill as Worker FE	
	Cross-Section	Life Cycle	cross-section	Life Cycle
Log of Size	-0.042***	-0.057***	0.002	-0.091***
	(0.005)	(0.008)	(0.010)	(0.011)
Constant	0.352***	0.534***	1.245**	1.049***
	(0.043)	(0.042)	(0.514)	(0.109)
Observations	185,263	185,263	177,503	177,503
R-squared	0.279	0.723	0.199	0.803
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Establishment FE	No	No	Yes	Yes

Notes: Includes age fixed effects. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

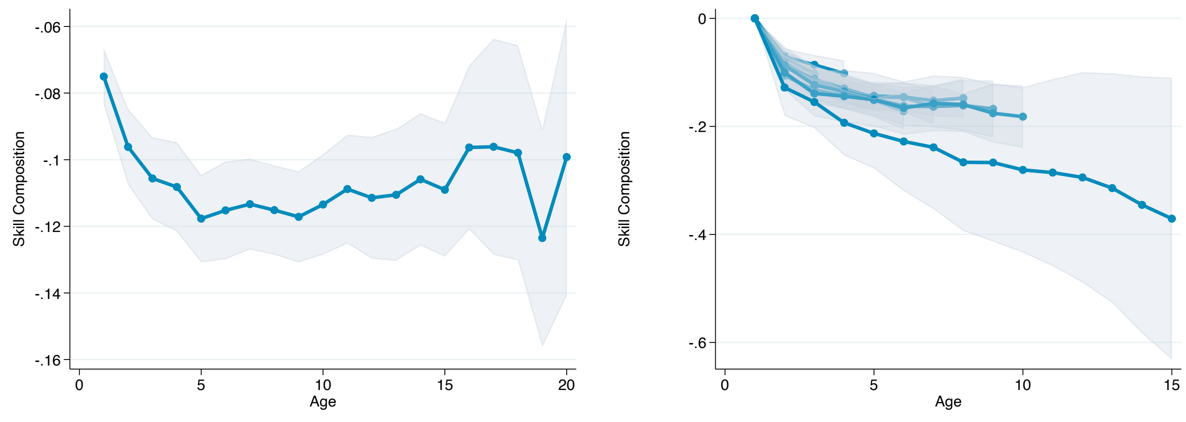

Figure A.10: Skill as Share Coll & Age in the cross-section Regression: Establishments Born with Coll

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

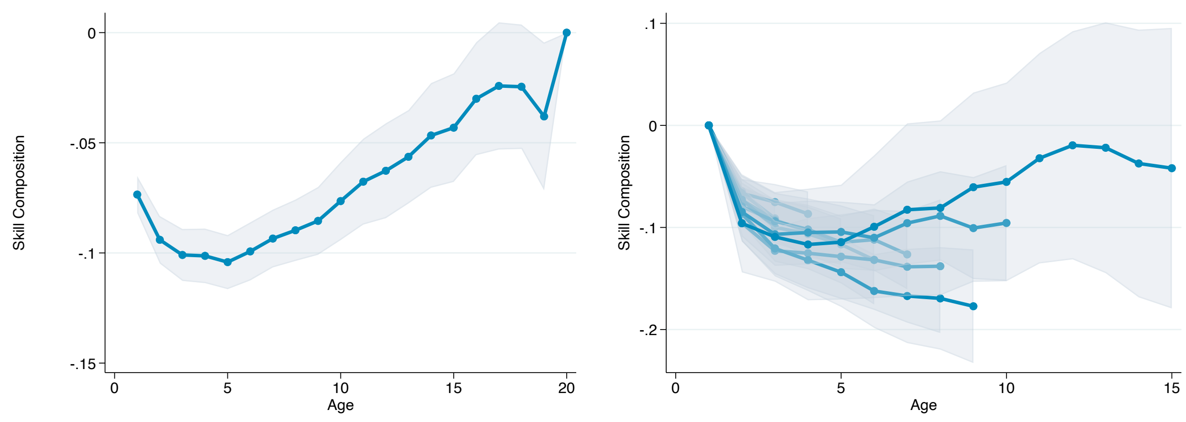

Figure A.11: Skill as Share Coll & Age in the Life Cycle Regression: Establishments Born with Coll

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

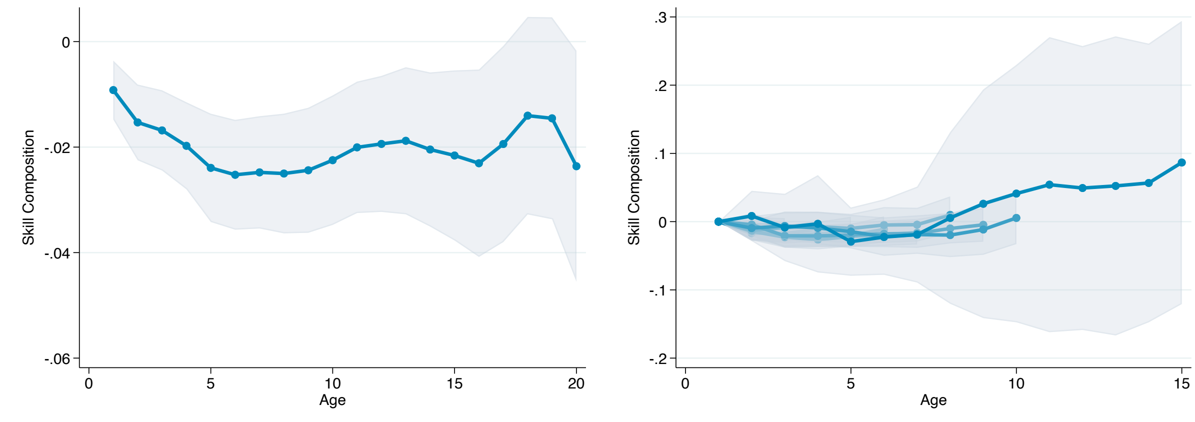

Figure A.12: Skill as Worker FE & Age in the cross-section Regression: Establishments Born with Coll

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

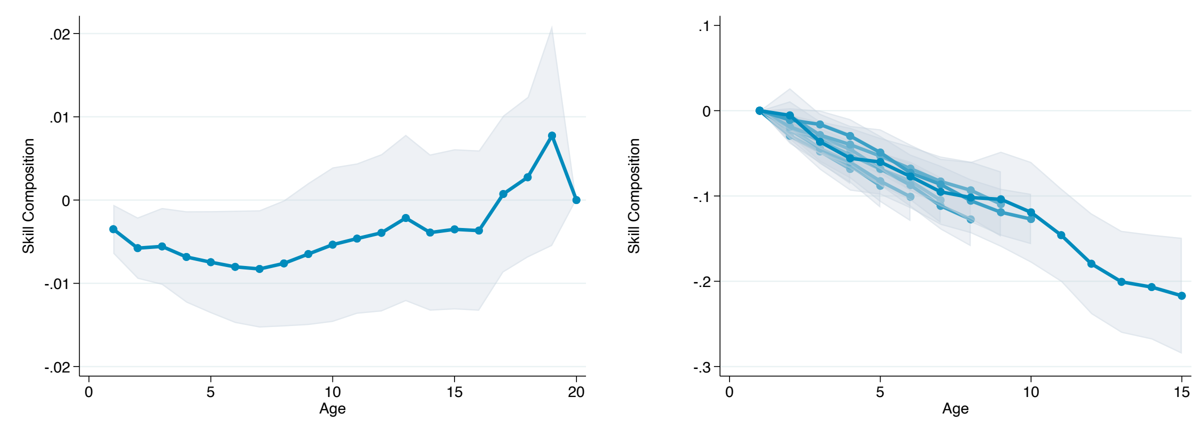

Figure A.13: Skill as Worker FE & Age in the Life Cycle Regression: Establishments Born with Coll

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

A.5.3 Empirical Results for the Full Sample of Establishments

Below, I present the empirical results estimated on the full sample of establishments. Similarly to the full sample of firms, the majority of the results are qualitatively similar to the the main results, with the exception of Figure A.15. In Figure A.15, we can see that using the share of college educated workers in the establishment as the average measure of skill in the establishment, the average skill level in the establishment increases as establishments age when we look at a balanced panel of establishments. This is not the case when we consider a more sophisticated measure of skill, namely the average worker FE in the establishment, as in this case the results are consistent with the main results of Chapter 1. One possible explanation is that these results are driven by establishments that hire at least one college educated worker as they age, which they are more likely to do the later we go in the sample, given that the overall share of the population with a college degree increases throughout the studied period. As time goes by, the share of college educated workers in the establishment as a measure of skill might become less informative, as opposed to the alternative measure of skill, that should not be subject to this concern.

Table A.5: Worker Composition and Size: Full Sample of Establishments

	Skill as Share of Coll		Skill as Worker FE	
	Cross-Section	Life Cycle	cross-section	Life Cycle
Log of Size	0.003**	-0.005***	0.039***	-0.012***
	(0.001)	(0.002)	(0.004)	(0.003)
Constant	0.017	0.032***	0.114	0.173***
	(0.011)	(0.006)	(0.105)	(0.013)
Observations	1,555,315	1,555,315	1,465,658	1,465,658
R-squared	0.21	0.70	0.20	0.75
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Est FE	No	No	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

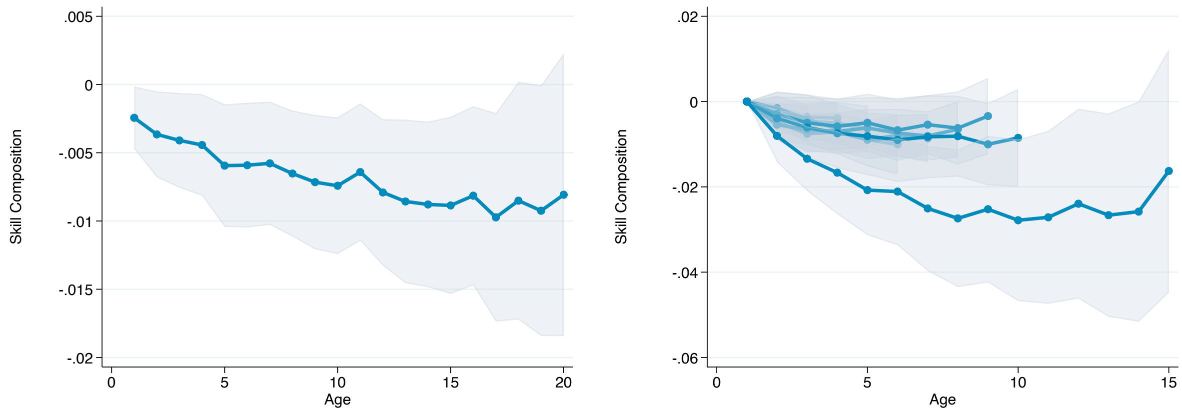

Figure A.14: Skill as Share Coll & Age in the cross-section Regression: Full Establishment Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

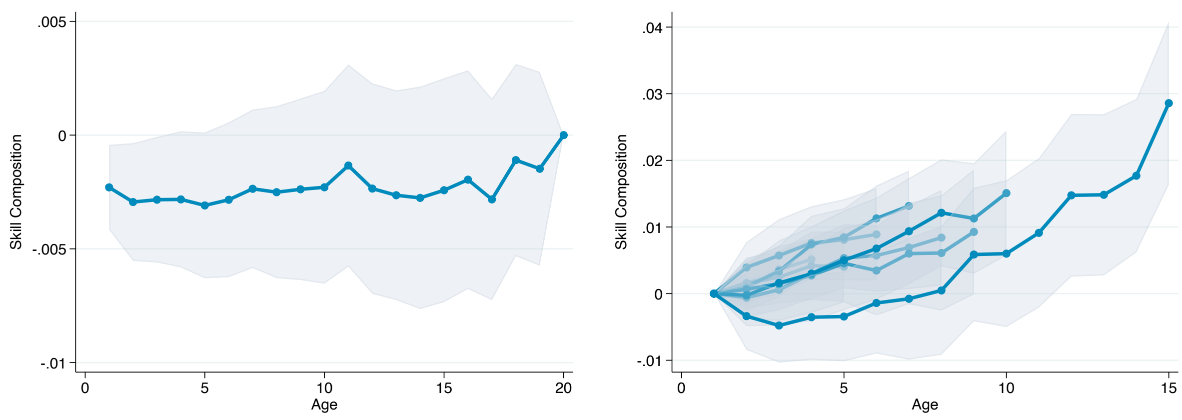

Figure A.15: Skill as Share Coll & Age in the Life Cycle Regression: Full Establishment Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of share of Coll workers on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

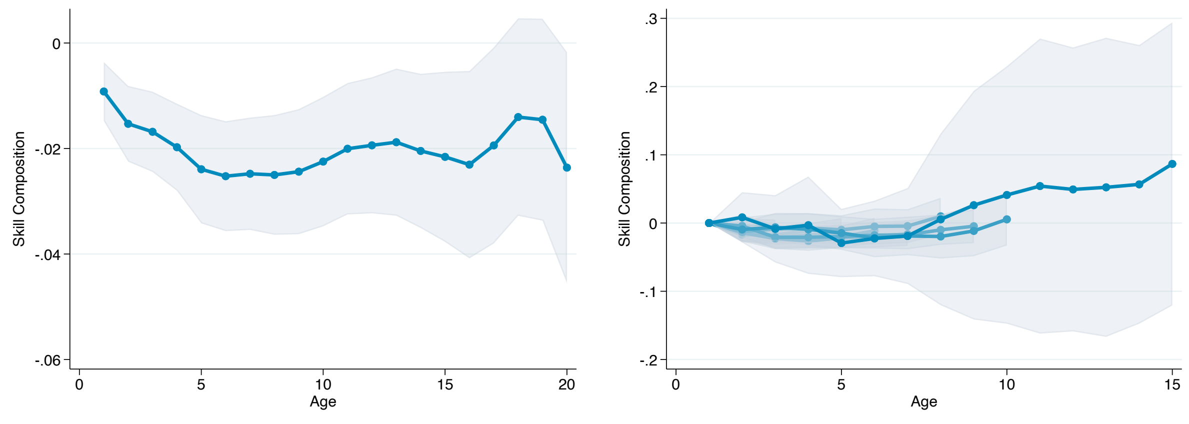

Figure A.16: Skill as Worker FE & Age in the cross-section Regression: Full Establishment Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.8), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

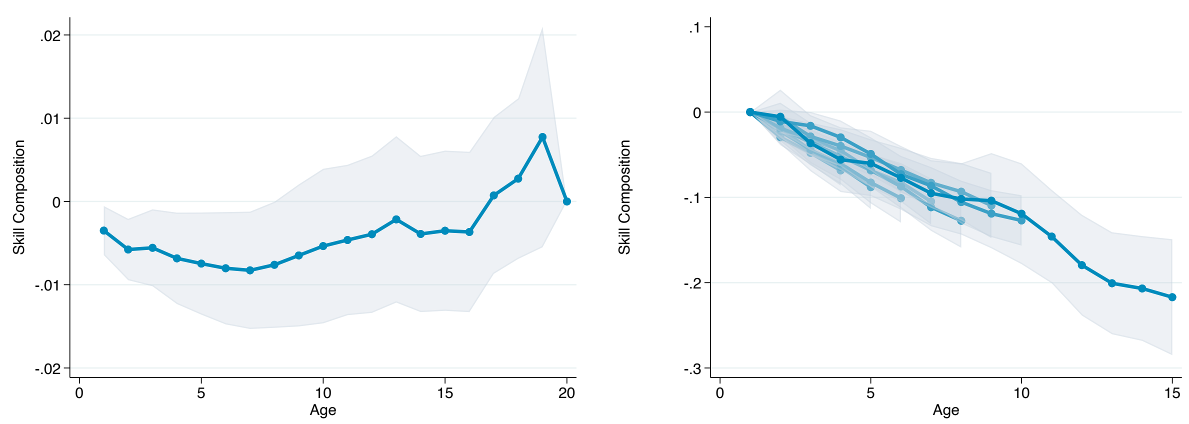

Figure A.17: Skill as Worker FE & Age in the Life Cycle Regression: Full Establishment Sample

Notes: Each dot in the graph represents a coefficient of a given age FE in the regression of the average skill level in the firm measured as the average of Worker FEs on the fixed effect of age (as per equation 1.9), with the 95-% confidence interval. The left panel shows the result of the regression in an unbalanced panel of firms. The right panel shows the age FE coefficients from separate regressions on subsets of firms that survive until a given age: survival ages 2-10 and 15. Most lines overlap as there is little difference in the relationship between worker skill composition and age by firm survival age.

Appendix B

Appendix for Chapter 2

B.1 Results for the Full Sample of Firms

Table B.1: Log of Wages: Full Sample

Log of Size	0.04***	-0.01***
	(0.004)	(0.002)
Constant	-0.349***	-0.440***
	(0.037)	(0.015)
Observations	1,409,247	1,409,247
R-squared	0.446	0.834
Year FE	Yes	Yes
Region FE	Yes	No
Industry FE	Yes	No
Firm FE	No	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

Table B.2: Change in Shares with Change in Size: Full Sample

	Industry FE			Firm FE		
	% Prim	% HS	% Coll	% Prim	% HS	% Coll
Log of Size	-0.004	0.002	0.002	0.002	0.003	-0.005***
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)
Constant	0.808***	0.165***	0.027**	0.759***	0.194***	0.047***
	(0.018)	(0.017)	(0.011)	(0.044)	(0.039)	(0.015)
Observations	1,412,267	1,412,267	1,412,267	1,412,267	1,412,267	1,412,267
R-squared	0.305	0.248	0.205	0.717	0.679	0.682
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

Table B.3: Log of Wages by Groups: Full Sample

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.035***	0.048***	0.080***	-0.001	-0.000	-0.002
	(0.003)	(0.003)	(0.006)	(0.001)	(0.001)	(0.003)
Constant	-0.162	-0.139	0.455	-0.116**	0.030	-0.216
	(0.097)	(0.179)	(0.300)	(0.052)	(0.140)	(0.268)
N	1,114,579	1,075,825	301,361	1,114,579	1,075,825	301,361
R-squared	0.433	0.365	0.241	0.782	0.777	0.815
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

Table B.4: New Hires and Stayers Average Wages: Full Sample

	New Hires		Stayers	
	Ind FE	Firm FE	Ind FE	Firm FE
Log of Size	0.040***	0.003	0.05***	0.01***
	(0.003)	(0.003)	(0.004)	(0.002)
Constant	-0.191**	-0.195***	0.19	0.70***
	(0.094)	(0.015)	(0.216)	(0.010)
Observations	1,150,126	1,150,126	1,114,229	1,114,229
R-squared	0.400 0.744	0.42	0.82	
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	No	Yes	No
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

Table B.5: Change in Shares for New Hires with Change in Size: Full Sample

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	-0.001	-0.001	0.002**	0.012***	-0.006***	-0.005***
	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Constant	0.76***	0.09***	0.15***	0.64***	0.17***	0.20***
	(0.039)	(0.025)	(0.038)	(0.065)	(0.058)	(0.056)
Observations	1,148,689	1,148,689	1,148,689	1,148,689	1,148,689	1,148,689
R-squared	0.25	0.20	0.17	0.59	0.55	0.52
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

Table B.6: Change in Shares for Stayers with Change in Size: Full Sample

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	-0.007***	0.003	0.004***	-0.004**	0.005***	-0.002*
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Constant	0.64***	0.13**	0.23**	0.60***	0.18***	0.222**
	(0.16)	(0.05)	(0.11)	(0.11)	(0.05)	(0.09)
Observations	1,102,593	1,102,593	1,102,593	1,102,593	1,102,593	1,102,593
R-squared	0.30	0.28	0.21	0.73	0.69	0.71
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

Table B.7: Log of Starting Wages by Groups: Full Sample

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Size	0.03***	0.05***	0.08***	0.01***	0.011***	0.01***
	(0.003)	(0.003)	(0.006)	(0.002)	(0.001)	(0.005)
Constant	-0.15	-0.04	0.50*	-0.13**	0.21	-0.27
	(0.097)	(0.247)	(0.268)	(0.051)	(0.145)	(0.314)
Observations	812,672	820,184	171,897	812,672	820,184	171,897
R-squared	0.41	0.35	0.24	0.72	Âă 0.71	0.75
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

Table B.8: Log of Stayers Wages by Groups: Full Sample

	Industry FE			Firm FE		
	Prim	HS	Coll	Prim	HS	Coll
Log of Size	0.04***	0.06***	0.09***	0.01***	0.01***	0.01**
	(0.003)	(0.004)	(0.006)	(0.001)	(0.001)	(0.004)
Constant	0.16	0.30***	0.65	0.32*	-0.52***	0.73***
	(0.19)	(0.02)	(0.68)	(0.19)	(0.13)	(0.16)
Observations	882,037	851,051	216,053	882,037	851,051	216,053
R-squared	0.40	0.35	0.25	0.76	0.77	0.82
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level.
$*p < .10, **p < .05, ***p < .01$.

Table B.9: Predictive Power of Size and Wages at Birth: Full Sample

VARIABLES	Size at 0	Size at 1	Size at 3	Size at 5	Size at 10	Size at 15	Size at 19
Entry Size		0.65***	0.46***	0.39***	0.33***	0.31***	0.30***
		(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)
Entry Wage	0.34***	0.17***	0.19***	0.17***	0.16***	0.15***	0.08
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.05)
Entry HS%	-0.11***	0.03***	0.05***	0.07***	0.10***	0.10***	0.04
	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.06)
Entry Coll%	-0.50***	0.10***	0.20***	0.24***	0.31***	0.40***	0.51**
	(0.08)	(0.03)	(0.04)	(0.05)	(0.08)	(0.12)	(0.20)
Constant	1.46***	0.80***	0.58	1.51***	1.72***	1.73***	2.34***
	(0.13)	(0.07)	(0.89)	(0.04)	(0.06)	(0.09)	(0.21)
Observations	211,055	173,397	132,016	99,270	49,115	20,165	4,695
R-squared	0.12	0.50	0.31	0.26	0.22	0.24	0.28
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Includes age FE. Standard Errors clustered at the industry level. $*p < .10, **p < .05, ***p < .01$.

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