Essays in Development Macroeconomics

Inauguraldissertation
zur Erlangung des akademischen Grades
eines Doktors der Wirtschaftswissenschaften
der Universität Mannheim

vorgelegt von

Vahe Krrikyan

im Frühjahrssemester 2019

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Tag der Verteidigung: 17. Mai 2019

Acknowledgements

First and foremost, I would like to thank my supervisors Klaus Adam and Sang Yoon (Tim) Lee for their invaluable support and feedback. Their continuous guidance helped me to stay focused throughout my PhD. I am very thankful to Klaus Adam for his thoughtful comments and discussions, and for giving me freedom to pursue my research interests. Tim has always been ready for valuable advice and suggestions, his constant encouragement and inspiration, his dedication as a mentor have helped me a lot in improving the chapters of this thesis.

I would like to express my deep gratitude to Michéle Tertilt for all her support and constructive comments, and for making my research visit to Minneapolis Fed possible. I would also like to thank Antoine Camous, Antonio Ciccone, Georg Duernecker, Sebastian Findeisen, Andreas Gulyas, Matthias Mand, Matthias Meier, Johannes Pöschl, Krzysztof Pytka, Minchul Yum, and all other members of the Mannheim Macro group for the insightful feedback and discussions.

My visit to the Minneapolis Fed helped me to look at my research from a deeper perspective. I would like to thank Alessandra Fogli and Todd Schoellman for hosting me and for their valuable feedback. I am also thankful to Anmol Bhandari, Kyle Herkenhoff, Loukas Karabarbounis, Ellen McGrattan, Fabrizio Perri, James Schmitz Jr. and then PhD students J. Carter Braxton, Guillaume Sublet, Jorge Mondragon for the extremely helpful discussions.

My friends at the CDSE made my PhD experience even more enjoyable. I am very thankful for the time we spent together. In particular, I would like to thank Tobias for his companionship in always planning but (almost) never actually playing football, my gym buddies Justin and Xin for our long conversations about economics and life, and Florian and Hanno for being excellent office mates. I am also thankful to Corinna Jann–Grahovac, Marion Lehnert, Claudius Werry and the Welcome Center team for their assistance in different administrative issues.

My parents Ruben and Naira, my brother Harut and my wife Ani have been there for me during this whole journey. They have shared with me all my achievements and failures

and have always believed in me. I have always felt their unconditional love and support, and I am very thankful to my family for that.

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Chapter 1

Preface

Understanding the main reasons behind the large and persistent differences in development and output per worker across countries has been a pressing objective for macroeconomists during the last decades. The seminal studies by Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) largely contributed to our understanding of these differences. They formally showed that country level differences in measured total factor productivity (TFP) play a key role in explaining the cross country variation in output per worker. This meant that, contrary to previous beliefs, mere accumulation of production resources cannot close a significant part of the gap in the international differences in output per worker.

These studies considerably advanced our knowledge of the main causes for international differences in growth and development. They gave forth to a new line of research that aimed at exploring the reasons behind the differences in the efficiency, with which countries combine human capital and physical capital to produce output. The works by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) were among many to study these reasons. They showed that the allocation of capital and labor resources among production units can produce a significant effect on the total factor productivity of an economy. This suggests that country development and country level output per worker may not only depend on the resource abundance of the country, but also on how these resources are distributed among the production plants.

These findings were important in the following way: they implied that if there exist frictions that distort the resource allocation process in the economy, then identifying these frictions, and policy interventions aimed at eliminating them will allow the market to reallocate the resources more efficiently. This reallocation process may increase the TFP and the country welfare. Thus, a new direction has emerged in the macroeconomic development literature that studies the resource allocation processes in developing, versus developed countries. The main objective of this literature is to identify the frictions that may cause resource misallocation and to estimate the magnitude of their effects on the country level TFP. My work stands in this realm of the economic literature.

This dissertation consists of two self-contained chapters. Each of the chapters studies a specific friction that can lead to resource misallocation and affect country level TFP through the occupational choice channel. I develop two theoretical models that capture the core peculiarities of these frictions and use the models to quantitatively analyse the importance of the frictions in explaining international differences in productivity.

Chapter 2: Family Firms and Talent Misallocation

Contrary to the previous belief that large firms are owned by dispersed owners, La Porta et al. (1999) has found that most large firms around the world are either state or family owned. This is true especially for developing countries. In this chapter, I first show that among European countries there is a strong negative correlation between the share of firms with single ultimate owner and country level development, measured by real GDP per capita. Furthermore, using the World Management Survey database, I find that in the universe of medium sized manufacturing firms, the share of firms that are solely owned by a family and are managed by a Chief Executive Officer, who is a member of the owner family, decreases with country level measured total factor productivity. I then propose a mechanism that can explain this relationship. In particular, several authors have suggested that the concentration of firm management and ownership within families can be due to high monitoring costs associated with hiring an external manager (e.g. Bandiera et al., 2011; Bloom et al., 2013; Burkart et al., 2003). In an economy where these costs are high, the owners of family firms may prefer a less qualified family member to a professional manager for the firm management role. Thereby, the concentration of firm ownership and management inside the family can lead to managerial talent misallocation, which will further result in losses in the country level TFP. The latter relationship is backed by the finding in the empirical literature that firm performance increases with hiring an external professional CEO. Furthermore, the higher are the costs of hiring an external manager, and/or the higher is the share of family firms in the economy, the larger will the TFP losses due to managerial talent misallocation be.

I develop a quantitative model of occupational choice to study the importance of managerial talent misallocation in explaining cross-country differences in measured TFP. The model is built on the differential rents mechanism by Sattinger (1979). The mechanism is augmented to allow for heterogeneous outside options for project owners and is embedded into a small open economy model with Lucas (1978) span of control production technology.

In the model, agents have heterogeneous managerial talents, and a given share of them is endowed with projects of varying quality. In order to start a firm and gain access to a production technology, a project owner either can combine the project with her own managerial talent and manage the firm herself, or she can hire an external manager and pay a fixed hiring cost. In the latter case, the profit is shared between the owner and the manager according to the differential rents mechanism. The model can thus generate different shares of owner managed firms, which is relevant for the analysis.

I calibrate the model to match several stylized facts of the US manufacturing sector. I then run a counter-factual analysis to study the model predicted losses in TFP due to managerial talent misallocation for a given group of countries. I find that the proposed channel alone can explain from five to 40 percent of the cross-country TFP difference, relative to the US. This finding emphasizes the significance of the costs family firms face when hiring managers in developing countries and it calls for developing policies aimed at lowering them.

Chapter 3: Occupational Choice, Social Insurance and Endogenous Financial Constraints

Entrepreneurs are mostly viewed as an important source of new ideas and innovative technologies in the academic literature. New start-ups account for a significant share of job creation in the developed countries. Meanwhile, many developing countries are characterized with high entrepreneurship rates, but also with low employment rates and low productivities. Why don't the high entrepreneurship rates in developing countries lead to the much needed creative destruction and job creation? Among many answers suggested by the economic literature, the following are the most accepted: (i) financial frictions in developing countries don't allow firms to invest and reach their optimal scale, and (ii) a large share of entrepreneurs in developing countries choose the occupation because they don't have other sources of income.

In chapter 3, I link these two explanations to answer the upper mentioned question. I develop a structural model where financial frictions faced by small and medium enterprises (SME) arise due to the information asymmetry between the lenders and the entrepreneurs, and depend on the composition of entrepreneurs. A high share of low skilled, necessity driven entrepreneurs can force the lenders to increase the borrowing interest rates. This will negatively affect the investment decisions of the opportunity driven entrepreneurs, distort the technology adoption decisions and decrease the total factor productivity. The social insurance plays an important role in the model, as it affects the occupational decisions. In particular, if the social insurance is low, the unemployed will spend less time searching for a new job and will become entrepreneurs out of necessity, driving up the borrowing interest rates and leading to capital misallocation. Additionally, as entrepreneurs don't receive job offers, the low social benefit will lead to misallocation of labor resources. The model captures the relationship between entrepreneurship rates, access to finance for SMEs and unemployment benefits I document in the cross-country data.

The model is based on the Lucas (1978) occupational choice model, with two important extensions. First, in my model agents can be employed only if they receive a job offer, otherwise they can stay unemployed and receive a social benefit. Agents can also become entrepreneurs, and those who choose the occupation because they didn't receive a job offer are defined to be necessity driven or subsistence entrepreneurs. Second, there is information asymmetry between the entrepreneurs and the lenders about the entrepreneurs' types, and given that the entrepreneurs can default on their loans, the lenders charge risk premia.

I calibrate the model to match several moments of the US economy. I then run a policy experiment where I feed the model with the average social benefits received by the unemployed in Chile. The model predicted occupational distribution is very close to the distribution observed in the Chilean micro-data. Furthermore, the model can explain around 55 percent of the average borrowing interest rate spread between SMEs and large firms in Chile. The consequent drop in investment, the distortion in occupational decisions and the resource misallocation decrease the output per worker. Only the occupational choice channel explains around 16 percent of the difference in output per worker between the US and Chile. I further conduct a robustness check for the case of Mexico and find similar results.

The analysis in this chapter implies that social insurance is not only important in providing a safety net for the poor, but it can also have large effects on resource allocation in labor and capital markets and thus, on the economy level productivity, especially in the developing countries.

Chapter 2

Family Firms and Talent Misallocation

2.1 Introduction

The observed large variation in per capita income across industrialized and developing countries has generated a large mass of research in recent decades. Total factor productivity (TFP) differences[1] have been shown to be the main driver of this variation (Hall and Jones, 1999; Klenow and Rodriguez-Clare, 1997). Subsequent work (e.g. Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009) suggests that the misallocation of production resources on the firm level can generate sizeable losses in TFP. In this paper, I suggest that family firms can be a source of managerial talent misallocation when they concentrate the ownership and management of the firm within the family. I quantitatively analyse the role of this channel in the cross-country differences in measured TFP.

Family firms are widespread around the world. They comprise not only of small and medium enterprises but also of multinational firms such as Samsung, Wal-Mart and Ford Motor. In comparison to firms of other organizational forms, family firms are peculiar in the sense that the owners can assign a member of the family as the Chief Executive Officer (CEO) of the firm. This can help them to avoid the conflict of interest between the owners and the management. The side effect of this characteristic is that the managers who are members of the family may not be as experienced and competent as an outsider professional CEO. Therefore, the decision to keep the firm management inside the family can potentially hurt the firm performance (e.g. Pérez-González, 2006; Bennedsen et al., 2007). Additionally, as I show in the empirical part of this chapter, family or individual ownership of the firm

[1] Total factor productivity is defined as the Solow residual, given a specific measurement of efficient units of production factors.

is the most common form of ownership in the developing countries. These facts make the analysis of family firms relevant from the development point of view.

I propose the following mechanism: In comparison to firms of other organizational forms, the owners of family firms can choose whether to assign a family member as the manager of the firm or to hire an external manager. If hiring an external manager is costly, some share of family firm owners will find it optimal to concentrate firm ownership and management inside the family, even when the family manager has a lower managerial talent than the external manager. These individual decisions of firm owners can affect the TFP through the following two channels. On the extensive margin, if hiring an external manager is costly, it will reduce the demand for external managers, forcing the latter to change their occupations. On the intensive margin, high hiring costs will make low talented firm owners reluctant to delegate the management to external CEOs, creating a mismatch between the firms and the managers. The resulting misallocation in managerial talent on the macro level will lower the TFP. In countries with higher hiring costs or a higher share of family firms or both, the concentration of firm ownership and management will be more severe. Higher concentration will lead to further misallocation of managerial talent and thus to a stronger decline in the measured TFP.

To further explore the mechanism and its effects, I develop a model, based on the differential rents mechanism by Sattinger (1979). I allow for heterogeneous outside options for project owners and embed the assignment problem into a small open economy model with Lucas span-of-control production technology. The agents in the model are endowed with heterogeneous managerial talents, and a given share of them have projects of varying quality. A firm in the model is the combination of a managerial talent and a project, with a decreasing returns to scale production function. Every project owner is also endowed with a managerial talent and she can choose either to use her own managerial talent to operate the firm, or to hire an external manager in the market for managers. In the latter case, the project owner incurs a cost of hiring[2]. I will refer to firms owned and managed by the same

[2]The literature proposes several types of costs family firms face when delegating management to an outsider, the agency problem being the primary source (Jensen and Meckling, 1976). In particular, the misalignment of the objectives of the firm owner (the principal) and the external manager (the agent) creates a need for monitoring by the owner, which is costly, especially in developing countries (e.g. Burkart et al., 2003). Bloom et al. (2013) find that one of the reasons why firm owners in India don't hire external managers is that they are uninformed about potential managers, and obtaining information may be costly. Demsetz and Lehn (1985), on the other hand, suggest the forgone 'amenities' from owning and managing the firm as another reason for the owners not to be willing to hire an external manager. In this chapter, I don't take a stance on which of these channels is the most important in developing countries, due to the lack of available data. Thus, the reader can think of the hiring cost in the model as a composite of the costs mentioned above.

agent as family managed firms (or owner-managed firms), and firms with a hired manager as firms with delegated management[3].

I show that adding these features in an otherwise standard assignment mechanism preserves the equilibrium outcome of positive-assortative sorting in the market for managers. It only affects the choices of project owners to participate in the assignment problem. In this model, the main parameter of interest is the cost of hiring, as it affects the endogenous decisions of project owners to hire an external manager and hence, the level of concentration of management and ownership in the economy.

The decision of the owner whether or not to hire an external manager depends on the following: her type (her managerial talent and the quality of the project she is endowed with), the distributions of managerial talents and projects in the economy, and the cost of hiring. The higher the project quality is, the higher the managerial talent of the owner needs to be for her to find it optimal to manage the firm on her own. The high cost of hiring will lead to misallocation of managerial talents in the model on the extensive and intensive margins. It will affect the average firm productivity and thus, the TFP.

To quantify the effects of talent misallocation, I calibrate the benchmark model to match several data targets of the US manufacturing economy. In particular, I use the model implied firm and managerial wage distributions to match targets of the corresponding distributions from the manufacturing sector. As the concentration of firm ownership and management is of central interest in this paper, I use the firm ownership and management data from the World Management Survey and the Survey of Business Owners to obtain data targets for calibrating the share of family-managed firms among firms of different size groups. In a counter-factual analysis, I study how the variation in the cost of hiring leads to endogenous changes in the share of family-managed firms in the model economy and to changes in TFP. As I do not directly observe the cross-country differences in the costs of hiring, I choose them such, that the model implied share of family-managed firms with size larger than 100 employees equals to that observed in the cross-country data. Lastly, for a given set of countries, I calculate the share of TFP difference from the US level, using the implications of the model.

The proposed stylized model can generate around 12 percent decline in TFP. If the market for managers is completely shut down, the losses will reach 15 percent. Given that I concentrate on one particular mechanism, and the only underlying friction is the cost of hiring a manager, the mechanism I propose can be considered economically significant. The cross-country analysis shows that the proposed mechanism alone can explain between 5 (in

[3]All firms in the model are individual (family) owned. It needs to be emphasized that in the proposed theory, the misallocation of managerial talents does not come from the share of family firms directly, but rather from the concentration of firm ownership and control that it causes.

case of China) and 40 percent (for Italy) of the cross-country TFP difference from the US level.

The chapter is organized as follows: Section 2.2 reviews the related literature. In Section 2.3, I present empirical evidence on cross-country differences in the share of family firms and concentration of ownership and management. Section 2.4 presents the model. In Section 2.5, I discuss the calibration strategy. In Section 2.6, I run a cross-country analysis of the implied impact of ownership and management concentration on TFP. Section 2.7 concludes.

2.2 Literature Review

Until recently, it was commonly believed that the ownership structure of most firms corresponds to the image by Berle and Means (1932), i.e., firms are owned by small dispersed shareholders and firm ownership and control are separated. It was the seminal paper by La Porta et al. (1999) that first showed that Berle and Means type firms are not the rule but rather the exception around the world. La Porta et al. (1999) collected data on ownership of the largest firms in 27 industrialized economies and found that most firms in their sample were either state or family owned. Since then, many authors have studied firm ownership structure and its effects on firm performance in various countries. E.g. Claessens et al. (2000), Bertrand et al. (2008), Morck et al. (2000) document high concentrations of firm ownership and control in less-developed countries. Others (e.g. Bennedsen et al., 2007; Pérez-González, 2006; Bloom and Van Reenen, 2010; Bandiera et al., 2015) have found sizable effects on firm performance when the owner chooses to keep the management inside the family. Pérez-González (2006) studies the change in firm performance when the firm management is passed to an insider manager. He uses data on US Compustat firms and finds that firm performance drops by 20 percent on average in case if the succeeding CEO of a company is somehow related to its owners, or the incumbent CEO. Bennedsen et al. (2007) find similar results using Danish data. In line with this literature, in the model I assume that family firms always have an option to hire a better external manager. This assumption is relatively common in the theoretical literature on family firms (e.g Burkart et al., 2003; Bhattacharya and Ravikumar, 1997).

My work is also related to the literature on managerial frictions. Several papers in this literature study the aggregate effects of sub-optimal delegation of managerial authority to middle-level managers. Grobovsek (2016) develops a model where the agency problems, arising due to imperfect law enforcement, force firm owners to hire sub-optimal number of middle-level managers, which leads to losses in aggregate TFP. In another paper, Akcigit et al. (2016) propose the lack of delegation of managerial authority to be a key mechanism for firm dynamics in the developing countries. The difficulty of delegating managerial tasks to outsider managers forces entrepreneurs to solely concentrate on firm management, constraining their growth opportunities. In both papers, the main key to cross-country firm size differences is the cost of delegation.

My work is closer related to another strand of managerial frictions literature that concentrates on top level managers and managerial talent misallocation. Caselli and Gennaioli (2013) study the effects of financial frictions on TFP through two channels: capital misallocation and inefficient level of trade in projects between talented and untalented owners. Their framework allows for misallocation of managerial talent on the extensive margin as the projects are homogeneous. In their simulations, they find that financial autarky can lead to losses in TFP of around 30 percent, which is the combined effect of the two channels. In comparison to their work, I propose a new mechanism based on family firms' choice to concentrate firm ownership and management within the family due to costly delegation. The assumption of heterogeneity in project distribution allows me to study both the extensive and intensive margins of managerial talent misallocation. Also, given that the costs of hiring in my model only affect the choice to hire a manager, my estimation of the TFP losses can be attributed solely to managerial talent misallocation. My work is also related to Alder (2016) who studies the mismatch between firms and their managers and its effects on aggregate productivity. He calibrates the model using data on firm profits and managerial compensations derived from Compustat. As an addition to his work, I suggest the concentration of firm ownership and management by family firms as a significant source that can distort the optimal allocation of managerial talent within an economy. In my model, agents are endowed both with managerial talents and projects, and they have an option to hire a manager. This fact allows the calibration procedure to be better disciplined and, in the framework of the model, the cross-country TFP differences due to the suggested channel to be quantified. My model construction also helps me to use data on incomes of managers of all firm sizes in the calibration procedure.

Lastly, my work is related to the vast literature that studies resource misallocation and cross-country productivity differences. Buera et al. (2011), Midrigan and Xu (2014) study the effects of financial frictions on entrepreneurs on the extensive and intensive margins and the subsequent TFP losses, Banerjee and Moll (2010) and Moll (2014) study the persistence of resource misallocation due to financial frictions. Barseghyan and DiCecio (2011), Guner et al. (2008) show that firm size dependent policies can account for sizable cross-country income per capita and productivity differences. Trade policies and product market regulations have also attracted research as a possible source of resource misallocation.

2.3 Empirical Facts

It is well documented that, in the case of listed companies, the share of family owned firms in developing countries is higher than in industrialized economies (e.g. La Porta et al., 1999), and the ownership and control are rarely separated. Few data is available on ownership and management of non-listed firms even for developed countries. Thus, many authors conduct research either using data for a specific country (e.g. Morck et al., 2000; Amit and Villalonga, 2006; Bertrand et al., 2008) or using data on a sample of countries (e.g. Bloom and Van Reenen, 2010; Claessens et al., 2000). For this reason, in order to provide evidence that the concentration of firm ownership and management is stronger in developing countries also in case of non-listed companies, I use data from the following two sources: Amadeus database from Bureau van Dijk and the World Management Survey.

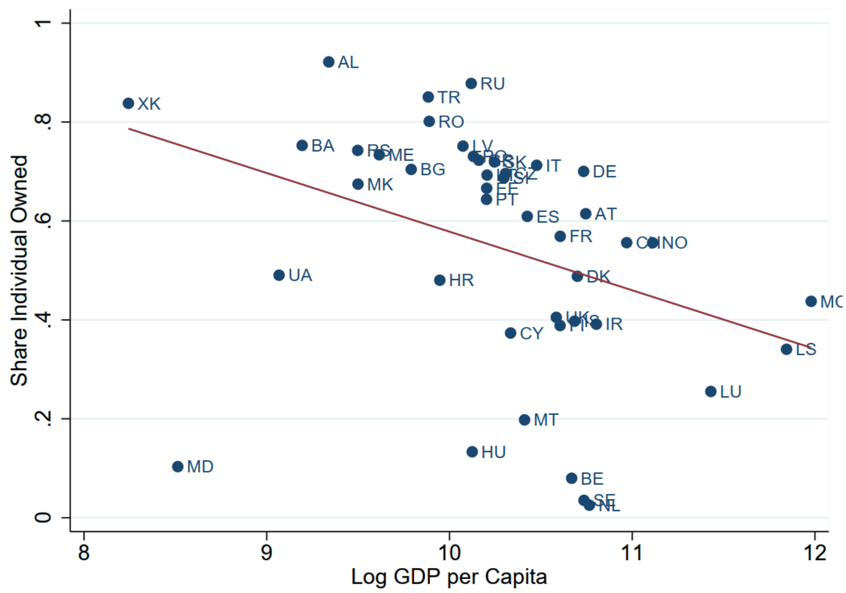
The Amadeus database is conducted by Bureau van Dijk. It contains comprehensive data on firm balance sheets, directors, corporate structures, etc. for more that 21 million firms registered in Europe. The database allows to identify the global ultimate owners of both listed and non-listed firms. The global ultimate owner of a given firm is defined as the entity or the person, that owns the firm either directly, or through a chain of ownership of other firms that own the firm. The database defines an individual or an entity as the owner of the firm if the former possesses the largest share of the firm that is larger that 25 percent.

Using the Amadeus database, I collect data on global ultimate ownership of very large, large and medium firms[4] in 43 European countries[5]. I omit the category of small firms from the analysis as small firms are not well represented in the database (e.g. Poschke, 2018a). For each country, in the sample of all firms in the country, I calculate the share of firms that are globally individual-owned. Figure 2.1 presents a scatter plot, where the share of individual owned firms by country is on the vertical axis, and the logarithm of per capita GDP is on the horizontal axis. The fitted line illustrates the negative relationship between the logarithm of country level GDP per capita and the share of individual owned firms, as a proxy of family ownership in the country. The OLS regression coefficient is -0.127 with a standard error of 0.048, indicating that even for a sample of only European countries the negative relationship between the share of family firms and the logarithm of per capita

[4]Here I use the firm size definitions used in the database. Firms are listed in the medium, large and very large size groups if they satisfy at least one of the following criteria: i) the operating revenue within a year is more than one million EUR; ii) the total assets are worth at least two million EUR; iii) the number of employees is at least 15.

[5]These countries are: Albania, Austria, Belgium, Bosnia & Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Macedonia FYR, Malta, Moldova, Monaco, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, UK and Ukraine. Data on Belarus is excluded because of the very small number of observations

Figure 2.1: The share of individual owned firms in the population of firms versus the logarithm of real GDP per capita for European countries.

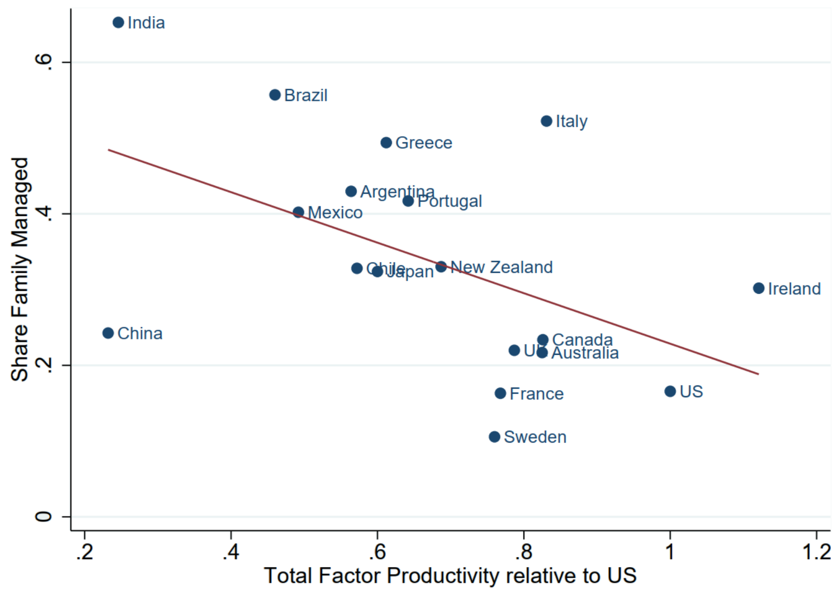


Sources: Amadeus database & CIA Factbook, year 2014. In Amadeus database, a firm is considered to be owned by an individual if the majority shareholder of the firm is an individual. The individual can own the majority shares either directly or through the ownership of other entities that own shares of the firm. The firm is defined to be owned by an entity if the latter holds ownership of the largest share of the firm, that is larger than 25 percent. The regression coefficient of the logarithm of per capita GDP is 0.127 with a standard error of 0.048.

GDP is statistically and economically significant. I also present the relationship between the share of employed in individual owned firms and GDP per capita across countries in the Appendix. The negative relationship between these two variables once again indicates the predominance of family firms in less developed countries. Naturally, this result only provides evidence that in less developed countries the share of individual or family owned firms is higher, but it doesn't say anything about the firm ownership and management concentration, as in many of the family firms the management could still be delegated to an external manager. Since Amadeus database doesn't provide any information about the relationship between the firm manager and the owners of the firm, for further analysis I use the data provided by the World Management Survey (WMS).

The WMS has been collecting data on managerial practices of firms around the world since 2002. The database includes data on samples of medium-sized manufacturing firms (with a size of between 100 and 5000 employees) from 34 developing and developed countries. The firms in the samples are randomly chosen, and a medium-level manager of each firm is contacted to answer specific questions on firm's managerial practices. The data set I am using has been collected during the years 2004-2010. It includes both ownership data and

Figure 2.2: The share of family managed firms in the total sample of firms by country versus the country level TFP relative to the US.



Sources: WMS years 2004-2010 & UNIDO World Productivity Database, year 2000. In the database, a firm is defined to be family managed if the CEO of the firm is a member of the owner family or is the founder herself. The regression coefficient is -0.77 with a standard error of 0.327.

data on managerial practices of more than 9200 manufacturing firms across 20 countries[6]. The firms in the sample can be grouped into four ownership categories: widely-held, family-owned, state-owned and other. The firms in the family-owned category can further be subdivided into founder-managed, family-owned and family CEO, and family-owned and external-CEO subcategories. In particular, the incidence of founder-managed, and family-owned and family-CEO firms in the sample of firms for each country in the global sample is of central interest in this analysis. I calculate the share of founder-managed, and family-owned and family-managed firms in the sample of firms for each country, and plot it versus the measured TFP of that country relative to the US. Figure 2.2 presents the results. The sample size is 18 observations, two observations are lost due to the lack of data on TFP. The negative slope of the fitted line is suggestive of the hypothesis, that firm ownership and management concentration in an economy negatively affects the TFP. The OLS regression coefficient on TFP is -0.77 with a standard error of 0.32 indicating that the relationship is statistically highly significant.

To conclude, in this section I first present evidence that in less developed countries the share of individual-owned firms is higher also for the case of non-listed firms. Naturally, this doesn't imply that firms owned by individuals also have managers related to the owners. Using the WMS database, I further show that at least for the case of medium-sized

[6]These countries are: Argentina, Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Italy, Japan, Mexico, New Zealand, Poland, Portugal, Republic of Ireland, Sweden, UK and the US

manufacturing companies, it is indeed the case that a much larger share of firms is managed by the relatives of the owners or the owners themselves in less developed countries, in comparison to developed countries. This finding implies that the underlying frictions, that lead to the concentration of firm ownership and management, are much more severe in developing, versus developed countries. Therefore, the managerial talent misallocation, resulting from the lack of delegation of firm management to outsider CEOs, can potentially explain a sizeable share of cross-country TFP differences.

2.4 The Model

The model economy is populated with a unit measure of agents. The agents are endowed with one unit of labor and they are heterogeneous in two dimensions: in their managerial talents and endowment with a project. The projects themselves are also heterogeneous in quality. All individuals are endowed with a managerial talent. The talents are denoted by z and are distributed according to some continuous distribution function $F_z(\cdot)$. In contrast, following Lee (2019) and Caselli and Gennaioli (2013), I assume that only a share λ_p of the agents are endowed with a project. The projects are drawn from a continuous distribution $F_p(\cdot)$. I allow for a correlation between the managerial talent of an agent and the quality of the project she is endowed with. The correlation parameter between the two distributions is denoted by ρ_{zp}.

The projects and managerial talents can be combined to start a firm. The firm then has a decreasing returns to scale production function. The productivity of the firm is a function of two variables: the managerial talent and the quality of the project that are combined. Consistent with the literature, I assume that the firm productivity is a supermodular function of its inputs, meaning that its cross-derivatives are positive. This assumption is crucial for later results as it leads to positive-assortative matching between outside managers and projects in the equilibrium. The economy is small open, and I assume that agents consume all current period income. Therefore, I concentrate on the steady-state of the model, and to avoid complications in representation, I omit the time indices.

Each project owner can either use her own managerial talent to operate the project, or hire a manager from the market for managers. In the latter case, I assume that the project owner's managerial talent does not play a role in the production process and only the outside manager's talent is used. In case of choosing to operate the project on her own, the owner who has managerial talent z^O and is endowed with a project p, operates the production technology given in (2.1) and keeps all the profit of the production process, given in (2.2).

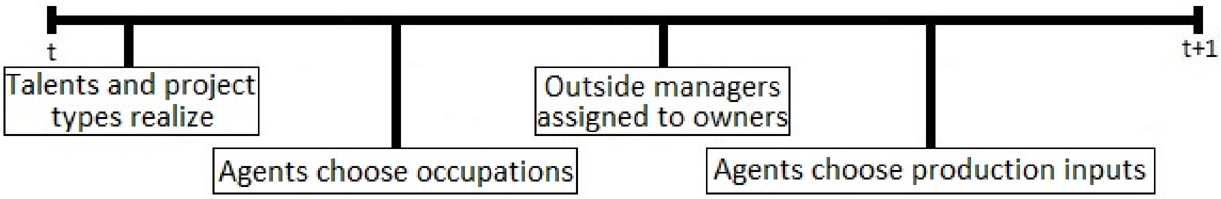


Figure 2.3: The timing of the decisions

$$y(z^O, p, k, l) = \phi(z^O, p)^{\nu}(k^{\alpha}l^{1-\alpha})^{(1-\nu)} \tag{2.1}$$

$$\pi(z^O, p) = \max_{k,l}\{y(z^O, p, k, l) - (\delta + r)k - wl\} \tag{2.2}$$

In case if the owner hires an external manager, they together choose how much to produce and share the generated surplus as in equation (2.3), where z^M is the managerial talent of the outside manager.

$$S(z^M, p) = \pi(z^M, p) = \omega(z^M, p) + Q(z^M, p) \tag{2.3}$$

The project owner receives compensation $Q(z^M, p)$, and the manager receives the managerial wage $\omega(z^M, p)$. When the project owner hires an external manager, she needs to pay a cost κ[7] and she has a free unit of labor that she can supply in the labor market and earn market wage w. One can think of this cost as a reduced form cost of monitoring associated with the moral hazard problem between the external manager and the owner.

On the other hand, the agents who do not possess a project can choose whether to supply their labor in the labor market, where they receive the market clearing wage w, or to enter the market for managers. The timing of the decisions made is given in Figure 2.3. The agents who supply their managerial talent in the market for managers face no cost of entry. Thus, they will choose to become managers if the managerial wage they are offered is at least as high as their outside option, which is the labor market wage. Here it needs to be mentioned that the labor market wage is an endogenous variable, therefore the agents' outside options depend on the fundamentals of the model.

Observing equation (2.3), one can notice that the surplus shares of the owner and the external manager are functions of only outside manager's talent and the project quality. This will be shown to be true in the competitive equilibrium of the market for managers, and the reason for this is as follows: Under the assumption, that the owner's managerial talent z^O doesn't influence the production output in case if the owner hires an external

[7]I assume that the cost of hiring is fixed for all project types. The model can easily incorporate a hiring cost $\kappa(p)$ that is a function of project quality.

manager, it can be shown that neither the compensation of the owner, nor the wage of the manager are functions of the owner's managerial talent. In other words, the owner's managerial talent doesn't affect her share of surplus but it only affects the decision whether to hire an external manager.

The potential managers and project owners meet in the market for managers. The details of the market for managers will be discussed in the following sub-chapter. All agents in the economy are perfectly informed about the ex-post market allocations and about their earnings, if they choose to enter either the labor market or the market for managers. Thus, in the stage of making occupational choice they have full information of the outcome.

In the model, the firm formed by a project owner when she chooses to operate the project by herself is equivalent to a family firm with an internal manager in the data. Thus, I will refer to these firms as owner-managed (or family managed) firms. In contrast, the firm formed by the project owner, who chooses to hire an external manager, will be equivalent to a firm whose manager and the owner are not related (firms managed by external managers) in the data.

After all the agents have made their occupational choices, and the market for managers has cleared, the owner-manager pairs choose how much output to produce. The first order conditions of the profit maximization problem are given in (2.4).

$$\begin{aligned} k^* &= \phi(z,p)\left(\frac{1-\nu}{\delta+r}\right)^{1/\nu}\left(\frac{(1-\alpha)(\delta+r)}{\alpha w}\right)^{\frac{(1-\alpha)(1-\nu)}{\nu}} \\ l^* &= \frac{(1-\alpha)(\delta+r)}{\alpha w}k^* \end{aligned} \tag{2.4}$$

From equation (2.4) one can observe that both inputs are linear functions of the firm productivity. This result will be useful for later derivation of the equilibrium TFP and the model calibration.

2.4.1 The Market for Managers

I model the market for managers using the differential rents mechanism by Sattinger (1979), first applied to CEO market by Tervio (2008). I extend the mechanism to incorporate the option for the project owners to manage the project by themselves. This extension creates heterogeneous outside options even for owners of similar quality projects. Thus, in contrast to the original set up, not all owners of a given quality project find it optimal to enter the market for managers, and their decisions depend on their managerial talents. As already mentioned above, this dimension allows me to have both owner-managed and external-manager-managed firms that are of the same size in the model, similar to the data.

Similar to the assignment mechanism by Tervio (2008) and the differential rents mechanism by Sattinger (1979), the managers' assignment to project owners will be positive-assortative in the managerial market equilibrium under the supermodularity assumption. This means that the best managers will be assigned to the owners of highest quality projects. The stability of the assignment in the equilibrium requires that the equilibrium managerial wages and compensations of the owners satisfy the participation, sorting and resource constraints. In particular, let's assume that in the equilibrium a manager with talent z^M is assigned to a project owner of type $\{z^O, p\}$. It should be the case then, that both the manager and the project owner get at least as much, as their outside options. In other words, their participation constraints, given by (2.5) & (2.6), need to be satisfied. Next, neither the manager nor the project owner can deviate to another match and be strictly better off, which means that the sorting constraints (2.7) & (2.8) need to be satisfied. And lastly, it should be the case, that the sum of the manager's wage and the owner's compensation does not exceed the total surplus they generate, meaning that the resource constraint (2.9) is satisfied.

$$\omega(z^M, p) \geq w \tag{2.5}$$

$$Q(z^M, p) - \kappa + w \geq \pi(z^O, p) \tag{2.6}$$

$$\pi(z^M, p) - \omega(z^M, p) \geq \pi(z'^M, p) - \omega(z'^M, p) \quad \forall\, z'^M \tag{2.7}$$

$$\pi(e^M, p) - Q(z^M, p) \geq \pi(z^M, p') - Q(z^M, p') \quad \forall\, p' \tag{2.8}$$

$$\pi(z^M, p) \geq \omega(z^M, p) + Q(z^M, p) \tag{2.9}$$

The main deviation from the standard mechanism comes in the participation constraint for the owners. It states that given a project of quality p, only those owners will choose to enter the managerial market, whose profits from managing the project are lower than their gains from entering. In particular, while the owners with low managerial talent will choose to hire an outside manager, owners with high managerial talents will choose to manage the projects themselves. And agents with no project will enter the managerial market if they are offered at least their outside option, which is the market wage. The equilibrium of the model is summarized in the following paragraph.

In the model equilibrium, for each project quality p there is a threshold managerial talent $z^O(p)$, such that the project owners with a talent higher than the threshold manage the project themselves. Those with below threshold talent either hire an external manager, or leave the project idle. The agents with no project and with a talent above a threshold managerial talent z^M supply their talent in the market for managers. In the market for managers, the assignment of the managerial talents of the external managers to the projects will be positive assortative and independent of owners' talents, given the supermodularity assumption.

This is because after the decisions to enter the market for managers have been made, the managerial talents and projects in the market for managers will be distributed according to some distribution functions $\chi_z(\cdot)$ and $\chi_p(\cdot)$ respectively, and the matching between projects and managers will be positive assortative (Sattinger, 1979). If equation (2.6) is not satisfied, the owner can walk away from the assigned pair and either leave the project idle and earn market wage w, or operate the project herself. The owner's talent doesn't affect the surplus generated when hiring an outsider, and this is why it plays no role in the assignment process after the participation decision has been made.

The measure of project owners willing to hire a manager needs to be equal to the measure of individuals with no project that enter the market for managers in the steady state. In order to simplify the representation of the equilibrium, it will be more convenient to refer to individual talents and projects in the market for managers by their percentiles in their respective distributions. In other words, let's define by $z^M[\iota]$ and $p[\iota]$ the managerial talent of the manager and the quality of the project on the ι-th percentile of their respective equilibrium distributions, such that $\chi_z(z^M[\iota]) = \iota$ and $\chi_p(p[\iota]) = \iota$. As already mentioned, given the assumption that $\phi(z, p)$ is supermodular, the assignment in the market for managers will be positive assortative (e.g Becker, 1973; Sattinger, 1979), which implies that the assigned pairs can also be identified by a single index ι. The results in (2.10) & (2.11) follow from the sorting constraints in (2.7) & (2.8), where $\omega[i, i]$ and $Q[i, i]$ are the wage and the compensation of the hired manager and the owner respectively.

$$\pi\left(z^M[i], p[i]\right) - \omega[i, i] \geq \pi\left(z^M[i-\epsilon], p[i]\right) - \omega[i-\epsilon, i] \tag{2.10}$$

$$\pi\left(z^M[i], p[i]\right) - Q[i, i] \geq \pi\left(z^M[i], p[i-\epsilon]\right) - Q[i, i-\epsilon] \tag{2.11}$$

These inequalities imply that the equilibrium managerial wage and compensation schemes must be such, that none of the members of the assigned pair have an incentive to deviate towards an agent on another percentile of the respective distribution.

2.4.2 Equilibrium Wages and Compensations

Naturally, whether $z^M[\iota]$ and $p[\iota]$ are continuous in ι depends on the assumptions on managerial talent and project distributions. For now I assume that they are continuous. The results don't depend on the continuity assumption, but it makes the derivations tractable.

The equilibrium wage and compensation schedules in the market for managers can be derived using the set of inequalities in (2.10) & (2.11). Dividing both sides of inequalities (2.10) & (2.11) by ϵ and taking it to zero in the limit, one can derive the following differential equations for the owner compensations and managerial wages:

$$Q_2'[i,i] = \frac{\partial \pi\left(z^M[i], p[i]\right)}{\partial p} p'[i] \tag{2.12}$$

$$\omega_1'[i,i] = \frac{\partial \pi\left(z^M[i], p[i]\right)}{\partial z^M} z^{M\prime}[i] \tag{2.13}$$

Equation (2.13) shows that the marginal change in the wage schedule for a manager at the i-th percentile depends on her marginal input in the profit, generated by the match, multiplied by the slope of the equilibrium talent distribution at i. The last term basically shows how substitutable the manager is in the market for managers. The flatter the managerial talent distribution at that point is, the more substitutable the manager will be with the adjacent managers and, thus, the lower her marginal wage will be. In other words, the marginal wage equation reflects both the manager's marginal input in generating the profit and the competition the manager faces for the given match from other managers with comparable talents. A similar logic holds for the marginal compensations of the project owners given in equation (2.12).

Adding initial value conditions to the differential equations in (2.12) & (2.13), one can derive the equilibrium wage and compensation schedules for the hired managers and owners respectively. We know that, given the managerial talents are continuously distributed, and only a share $\lambda_p < 1$ of the population is endowed with projects, the wage of the lowest talented manager hired in the market will be her outside option w. The lowest compensation the project owners get, on the other hand, depends on the assumed distributions of managerial talents and projects in the economy and is endogenously determined. It is an equilibrium outcome and will be calculated numerically. Let $\underline{Q}$ denote the lowest compensation that a project owner receives. Given that project owners are free to abandon their projects with no cost, $\underline{Q} \geq 0$. The resource constraint for the pair of the lowest type manager and project in the market for managers will be given by:

$$\pi\left(z^M[0], p[0]\right) = \underline{Q} + w \tag{2.14}$$

Now, using the initial conditions in (2.14) and the set of differential equations given in (2.12)

& (2.13), one can derive the equilibrium wage and compensation schedules.

$$\omega[i,i] = w + \int_0^i \frac{\partial \pi\left(z^M[x], p[x]\right)}{\partial z^M} z^{M\prime}[x]dx \tag{2.15}$$

$$Q[i,i] = \underline{Q} + \int_0^i \frac{\partial \pi\left(z^M[x], p[x]\right)}{\partial p} p'[x]dx \tag{2.16}$$

We can observe from equation (2.15) that the managerial wage is a non-decreasing function of managerial talent. Thus, in equilibrium there will be a threshold talent $\underline{z}^M$ such, that those with no project and with a managerial talent higher or equal to this threshold will become managers, while those with lower talent will supply their labor in the labor market. On the other hand, equation (2.16) shows that the compensation to the owners does not depend on their managerial talents. It only affects the decision to enter. This result is intuitive for two reasons. First, I assume that the firm productivity is a function of two variables: the owner's project quality, and the manager's talent. The owner's talent does not play a role, thus it does not affect the generated profit. Second, given that the project and managerial talent distributions are assumed to be continuous, conditional on project quality, the managerial talent distribution of owners of a given project is also continuous, which doesn't give room for market power and bargaining (e.g. Sattinger, 1979, 1993). So then the higher outside option of the owners does not translate to higher bargaining power for them, it only affects their decision whether to hire a manager.

We can also observe from (2.16), that the owner's compensation is a non-decreasing function of the project quality. Combining this result with the participation constraint in (2.6), for each project of quality p one can derive the threshold managerial talent $\underline{z}(p)$, that makes the project owner of type $\{\underline{z}(p), p\}$ indifferent between hiring an external manager and managing the firm herself. Given that the owner's equilibrium compensation is a function of only the project quality, the threshold managerial talent will solve the following equation:

$$\pi(\underline{z}^O(p), p) = max\{Q(p) - \kappa, 0\} + w \tag{2.17}$$

From equation (2.16), the owner's compensation is a weakly increasing function of project quality. This means that, all else equal, the higher the project quality is, the higher the threshold managerial talent for the owner will be. This result is in line with the findings by Bhattacharya and Ravikumar (1997) and Burkart et al. (2003), who show that the larger gains associated with hiring an external manager make the firm owner more willing to delegate the management to an outsider.

At the same time, the threshold talent $\underline{z}(p)$ for each project p is decreasing in κ. This implies that if it is costly to hire an external manager, only the project owners with low talent will choose to hire one. Hence, high costs of hiring will generate managerial talent misallocation on the intensive and extensive margins. On the extensive margin, the total measure of project owners willing to hire an external manager will decrease, which will lead to an increase in the threshold managerial talent $\underline{z}^M$. This means that a share of individuals with no project, who would be hired as managers if κ was low, will not enter the market for managers after the rise in the cost. On the intensive margin, we can see from equation (2.17) that an increase in the hiring cost will make the threshold managerial talent for the owners $\underline{z}^O(p)$ decline. This means that with an increase in κ, some share of project owners, who previously found it optimal to hire a manager, will now choose to manage the project on their own. The resulting mismatch between projects and managerial talents will lead to losses in TFP.

2.4.3 Equilibrium

Definition 1: The stationary equilibrium of the model is a price vector $P = \{w, Q(p), \omega(z^M)\}$, threshold managerial talents $\underline{z}^M$ and $\underline{z}^O(p)$ for all project qualities p, and the optimal capital and labor inputs $k^*(z,p)$ and $l^*(z,p)$ for the assigned pairs in the market for managers and for the owner-managers such, that given the prices:

(i) Individuals not endowed with a project choose their occupations optimally,

(ii) Project owners' choice to hire an external manager or to manage the project on their own is profit maximizing,

(iii) Each firm maximizes its profit, given by (2.2),

(iv) All assignments in the market for managers are stable, which means that none of the participants are willing to deviate from the assigned pair,

(v) The market for managers, given by equation (2.18), clears:

$$\int_{\underline{z}^M}^{z_{max}} dF_z(\tilde{z}|p=0) = \int_p \int_0^{\underline{z}^O(p)} dF_z(\tilde{z}|p)dF_p(\tilde{p}) \tag{2.18}$$

(vi) The labor market, given by equation (2.19), clears.

$$\begin{aligned} \int_{\underline{z}^M}^{z_{max}} dF_z(\tilde{z}|p=0)\int_0^1 l^*[i,i]di + \int_p \int_{\underline{z}^O(\tilde{p})}^{z_{max}} l^*(\tilde{z},\tilde{p})dF_z(\tilde{z}|p)dF_p(\tilde{p}) = \\ = \int_0^{\underline{z}^M} dF_z(\tilde{z}|p=0) + \int_p \int_0^{\underline{z}^O(\tilde{p})} dF_z(\tilde{z}|p)dF_p(\tilde{p}) \end{aligned} \tag{2.19}$$

The left-hand side of equation (2.18) is the supply of managerial talent by the individuals, who are not endowed with a project. The right-hand side of the equation is the demand for managerial talent in the market for managers.

In equation (2.19), on the left-hand-side the first term is the total labor demand of firms with external managers, and the second integral is the demand by owner managed firms. On the right-hand side of the equation, the first integral is the labor supply by those not endowed with a project, while the second integral is the labor supply of firm owners who choose to hire an external manager.

2.5 Calibration

I calibrate the benchmark model to match several data moments of the US manufacturing industry. I divide the model parameters into two groups. I take the values of the parameters in the first group from the literature, while the parameter values of the second group are chosen to minimize the distance between model predicted and empirical moments.

Similar to Alder (2016), I assume that the firm technology function is CES, with a share parameter γ and a substitution elasticity of $\frac{1}{1-\rho}$:

$$\phi(z,p) = (\gamma z^{\rho} + (1-\gamma)p^{\rho})^{1/\rho}$$

The assumption of CES technology function is convenient as, depending on parameter ρ, the project quality and the managerial talent can be modelled either as substitutes or as complements.

The fixed parameters and their values are presented in table 2.1. The interest rate r is set to be 4 percent and the depreciation rate δ is equal to 0.06. I take the capital share parameter α from Buera and Shin (2013) and set the span of control parameter ν equal to 0.15 in line with the findings by Atkeson and Kehoe (2005). Lastly, given that the elasticity of substitution between managerial talent and project quality has not been pinned down in the literature, I follow Alder (2016) and set it to be equal to 0.5.

Table 2.1: Exogenous Parameters

Parameters		Values	Reference
Capital share	α	0.28	Buera & Shin (2013)
Span of control	ν	0.15	Atkeson & Kehoe (2005)
Depreciation rate	δ	0.06	Buera & Shin (2013)
Net interest rate	r	0.04	Clementi & Palazzo (2016)
Elasticity parameter	ρ	-1	Alder (2016)

Table 2.2: Several empirical moments of the US CEO wage and firm size distributions

Wage Distribution		Firm Distribution	
Percentile Ratio	Value	Size	Percentile
$99^{th}/10^{th}$	11.68	$<$ 25 employees	76.6%
$99^{th}/25^{th}$	7.05	$<$ 50 employees	87.0%
$90^{th}/25^{th}$	4.63	$<$ 100 employees	93.2%
$90^{th}/50^{th}$	2.76	$<$ 500 employees	98.5%
$50^{th}/\bar{w}$	2.87	$<$ 5000 employees	99.8%

Sources: Author's calculations from IPUMS-USA for years 2010-2014, and Rossi-Hansberg and Wright (2007). $\bar{w}$ is the average labor market wage. The percent of firms with less than a given number of employees is presented in column "Percentile".

I assume that the managerial talents are log-normally distributed with mean and variance parameters μ_e and σ_e respectively. This assumption is common in the literature for modelling the distribution of human capital. Based on the finding that US firm distribution follows a power law (e.g. Axtell, 2001), I assume that the projects are Pareto distributed with scale parameter normalized to 1 and shape parameter η_p. This leaves me with additional seven parameters to calibrate, which means I need seven empirical moments to match the model with. I use the CEO income and firm size distributions in the US manufacturing industry to calibrate the distributional parameters. Table 2.2 presents several moments of these distributions.

The mean μ_e and the variance σ_e^2 of the log-normal distribution of managerial talents, and the shape parameter η_p of the project quality distribution govern the firm size and the CEO wage distributions in the model, through their effect on the assignment process in the market for managers. The variance controls the dispersion of managerial talents, and the mean affects the average talent in the market, and thus, the average firm productivity. Hence, I choose the $99^{th}\%/10^{th}\%$ CEO wage ratio and the median CEO wage - average wage ratio as empirical moments for the parametrization of the managerial talent distribution.

Table 2.3: Parameter choices and calibration targets[8]

Parameters	Values	Targets
μ_e	-1.88	99/10 CEO wage ratio*
σ_e^2	4.1103	Median CEO - avg wage ratio*
η_p	1.1226	$Pr(fsize < 100)$
γ	0.9021	CEO income share in profit
λ_p	0.015	Manu. firm share
ρ_{ep}	0.216	Family firm share ($> 100emp$)
κ	4.5	Family firm share ($< 20emp$)

Note: The CEO income share in the firm profit is calculated as the average share of CEO annual compensation in the annual profit of the firm, for the largest 0.3 percent of manufacturing firms in the number of employees.

I choose η_p such, that the model implied share of firms with less than 100 employees matches the data.

Parameter λ_p governs the share of agents who are endowed with a project. In the model, firms can be started only by project owners, but not all of them may decide to become a firm owner. This decision depends on the project quality and the assignment process in the market for managers. Therefore, λ_p also governs the share of the firms in the model. I choose this parameter to match the firm share of 1.13% in the data.

Finally, I need to assign values to the correlation parameter ρ_{zp} and the hiring cost κ. The correlation parameter affects the joint distribution of project qualities and managerial talents in the model. A high, positive value of ρ_{zp} makes the owners of high quality projects more likely to have managerial talents from the right tail of the talent distribution. In contrast, if the correlation coefficient is equal to zero, both for the low talented and for the high talented agents the likelihood of owning a high quality project is the same. It follows that if ρ_{zp} is high, a lower share of firm owners will find it optimal to hire an external manager, everything else equal, and vice versa.

Therefore, I choose the correlation parameter such, that the share of family managed firms of size larger than 100 employees in the benchmark model is 20%, as in the data. The hiring cost κ affects the decisions of firm owners to hire an external manager. Everything else equal, a high value of κ leads to higher equilibrium concentration of firm ownership and management. Hence, I choose κ to match the share of family managed firms of size smaller than 20 employees in the data. I calculate the share of manufacturing firms that

[8]The value of CEO income share in profit is from Alder (2016) and represents the average share of annual CEO compensations in firm profits for the firms above the 99.7th percentile of the manufacturing firm distribution

are managed by internal managers from the Survey of Business Owners (SBO) for the year 2007. Table 2.3 presents the set of parameters that are used for the calibration of the model, and their final values.

In order to make inference on CEO income distribution in the US, I use the IPUMS USA database for years 2010-14, which is a representative survey of US population. The database includes rich individual level data on the socio-economic characteristics of the US population, such as employment status, income, occupation, the industry the individual works in, etc.

I calculate the CEO income in the data set as the sum of ”Wage or salary income” and ”Interest, dividend and rental income” categories in order to also capture the part of CEO compensation coming from received stock options and grants. To calculate the CEO income distribution moments, I concentrate only on the data on individuals who have occupational code 0010 ”Chief Executives”, who work in the manufacturing industry and earn non-zero income. I drop all self-employed individuals, who in the model would be equivalent to individuals who manage their own projects, and I concentrate on CEO-s who are only employees of the firms they work at. The reason for this is that, given the data limitations, I cannot separately calculate the share of firm owners' incomes that come from their managerial talents and the share that come from the quality of the project they are endowed with. Given this, the empirical moments I calculate can be compared with the managerial wage distribution of the hired external managers in the model.

As already mentioned, I use the ratios of different percentiles of the CEO wage distribution and also the median CEO wage relative to the average wage in the manufacturing sector as the empirical targets for the model calibration. One drawback of using the IPUMS-USA database to calculate the empirical moments of CEO wage distribution is that the data on incomes is top-coded. This means that the empirical distribution of CEO wages derived from IPUMS-USA is only the truncated version of the actual wage distribution. In order to make correct comparisons of the CEO wage distributions in the data and in the model, I implement the following procedure: I first calculate the ratios of the percentiles of the CEO wage distribution in the data. I calculate the averages of these moments for the 2010-14 period. Next, I find the ratio of the highest CEO wage and the average wage in the data and use it to create a comparable truncated distribution of CEO wages in the model[9]. I then compare the empirical ratios with the percentile ratios of the model generated truncated distribution. The empirical moments of the CEO wage distribution in the manufacturing sector are presented in table 2.2.

[9]In particular, I use this ratio to calculate the CEO wage in the model that is equivalent to the highest top-coded wage in the data, and then I truncate the model generated CEO wage distribution from the right, using this wage as the truncation point.

Table 2.4: Model vs. data targets

Model	Data	Targets
11.27	11.68	$99^{th}/10^{th}$ CEO wage ratio
1.94	2.87	Median CEO wage - $\bar{w}$ ratio
86.78 %	93.2 %	<100 employees, percent
7.02%	7 %	CEO income share in profit
1.13 %	1.13 %	Share of manufacturing firms
21.76 %	20 %	Family firm share ($> 100emp$)
52.89 %	50 %	Family firm share ($< 20emp$)

Note: $\bar{w}$ is the average wage in the labor market. The manufacturing firm share in total employment in manufacturing is taken from Business Dynamics Survey (BDS). Family firm share in this table refers to the ratio of firms that are managed by the owners or their relatives and the total number of firms. The data on the share of family managed firms with more then 100 employees is taken from the World Management Survey (WMS), and the data on firms with less than 20 employees is calculated using the Survey of Business Owners (SBO), year 2007.

Table 2.5: Firm and Wage Distribution: Data vs. model

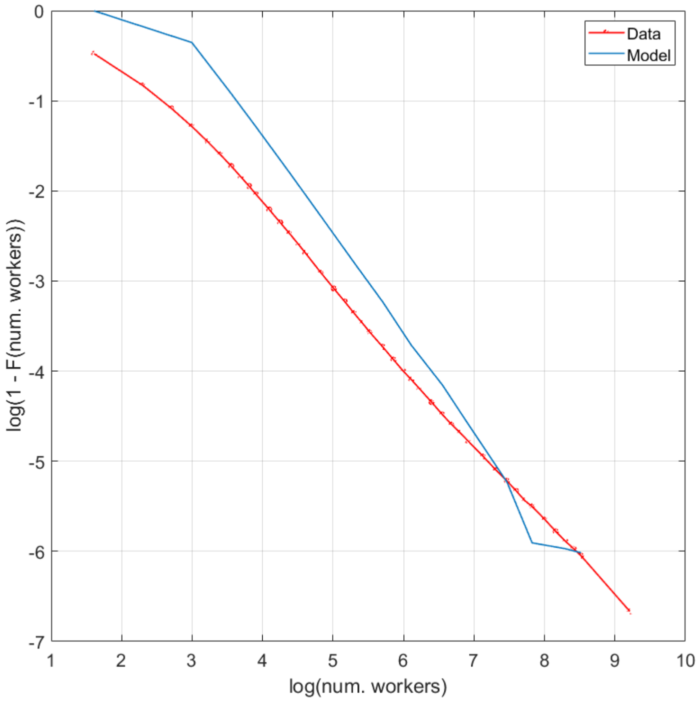
Firm Distribution			Wage Distribution		
Size	Data	Model	Ratio	Data	Model
$<$ 25 employees	76.6	43.7	$99^{th}/10^{th}*$	11.68	11.27
$<$ 50 employees	87.0	72.3	$99^{th}/25^{th}$	7.05	9.34
$<$ 100 employees*	93.2	86.8	$90^{th}/25^{th}$	4.63	3.93
$<$ 500 employees	98.5	97.8	$90^{th}/50^{th}$	2.76	2.75
$<$ 5000 employees	99.8	99.7	$50^{th}/w*$	2.87	1.94

Note: Targeted moments are indicated with an asterisk. The data on manufacturing firm distribution is taken from Rossi-Hansberg and Wright (2007). The information on the calculation of the ratios is presented in the text.

Table 2.4 presents the values of the empirical moments and the benchmark model performance. The model does well in hitting the empirical targets. While it generates a slightly lower share of firms with at most 100 employees, and the CEO wages are not as large relative to the average wage as in the data, but the CEO income share in firm profits, the CEO wage dispersion captured by $99^{th}/10^{th}$ percentile ratio and the total firm and family managed firm shares in the economy are quite well approximated. The benchmark model performance is satisfactory off target as well. Table 2.5 presents the non-targeted empirical moments and model's predictions.

As we can see from the table, the CEO wage distribution is well approximated by the

Figure 2.4: Model implied firm size distribution vs. data



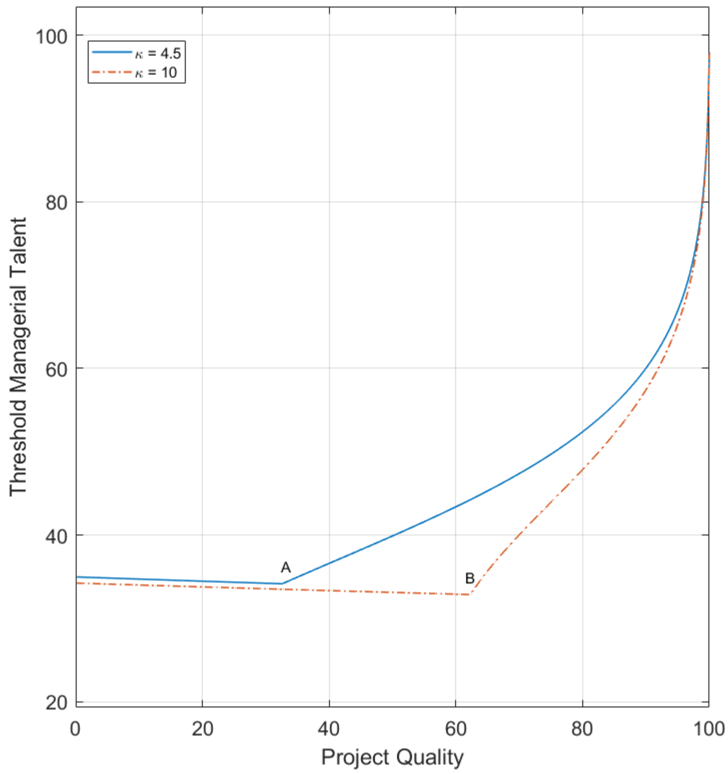
model, and in the data it seems a bit shifted upwards relative to the average wage in comparison to the model. The firm size distribution is more concentrated towards the right tail relative to the data. This means that large firms are over-represented in the model. This fact can also be noticed from Figure 2.4 which plots the firm size distribution in the data versus the distribution generated by the model. Overall it needs to be mentioned, that the fit of the model to the data is satisfactory given its stylized nature.

2.6 Results

The benchmark calibration produces a non-trivial cost of hiring, which is around three times larger than the market wage. This value is needed to match the fact that roughly 50% of US firms with less than 20 employees are managed by their owners. The calibrated non-zero cost of hiring implies that even in the US, hiring an external manager is associated with significant costs, which may or may not be worth paying for the firm owners.

To calculate the model implied productivity losses associated with managerial talent misallocation in the US, I set the cost of hiring $\kappa = 0$ and solve the model once again. In case with zero hiring cost, the share of small firms (less than 20 employees) with owner-managers drops by 20 percentage points, the share of large firms with owner-managers stays relatively the same, and the gains in the TFP are minimal. This is due to the fact, that

Figure 2.5: Threshold managerial talent of the owner as a function of the project she is endowed with



This plot shows the managerial talents of the project owners who are indifferent between hiring an external manager or managing the firm themselves, as a function of the project quality. On the axes, the managerial talents and the qualities of the projects are normalized to a scale from 0 to 100, where 0 indicates the lowest quality.

the calibrated value of the hiring cost is relatively low for the large firms in the benchmark model, and therefore it leads to a misallocation of managerial talents only in the small firms. Given that the productivities of large firms have higher weight in the total factor productivity, eliminating the hiring cost produces a low effect on the TFP.

I next use the benchmark model to study the effects of the increase in the hiring cost on the concentration of firm ownership and management in the economy, the resulting misallocation in managerial talent and its effects on total productivity. For illustration purposes, I choose the new value of hiring cost equal to 10, which is more than twice higher than the hiring cost in the benchmark model. The change in threshold managerial talents due to the increase in the cost of hiring is presented in Figure 2.5.

Figure 2.5 visualizes the threshold managerial talents of owners, as functions of project quality, that make the owners indifferent between hiring an external manager and managing the project themselves. The blue solid line presents the threshold managerial talents in the benchmark model, and the red dash-dot line is the threshold managerial talents in the model with a high cost of hiring ($\kappa = 10$). The project owners with managerial talent above the lines choose to operate the projects themselves.

We can notice that the threshold managerial talent is decreasing in project quality until point A (point B in the case of high cost of hiring), and increasing afterwards. Let us first concentrate on the part where the relationship is negative (to the left of points A and B). Due to positive assortative matching between projects and external managers in the equilibrium, the owners of low quality projects can hire only mediocre managers. Therefore, it will not be optimal for them to pay the hiring cost and delegate the management of the firm to an outsider. But then if their managerial talent is not high enough to generate profit higher than the market wage, they will leave the project idle and supply their labor in the labor market. Given the parametrization of the model, the lower is the project quality, the higher the owner's managerial talent needs to be in order to earn profit at least as much as the market wage. This generates the negative slope of the line to the left of points A and B. Furthermore, an increase in the cost of hiring will also increase the minimum required surplus that satisfies the participation constraints of the owner and the manager. But then the quality of the threshold project, the owner of which is indifferent between hiring an external manager and leaving it idle, will go up. This is the reason why point B lies to the right of A.

The positive relationship between managerial talents and project qualities to the right of points A and B in figure 2.5 is due to the following reason. As already discussed, the assignment between projects and external managers is positive assortative in the equilibrium, and the compensations to the owners are increasing in project quality. Therefore, everything else equal, the owners of higher quality projects, who are indifferent between hiring an external manager and managing the project themselves, will have higher managerial talents. Additionally, when the cost of hiring goes up, the owners' net compensations from hiring an external manager decrease. Hence, the threshold managerial talent that makes the owners of a project of a given quality indifferent between hiring and managing the firm themselves, also declines. This is the reason why the red line in figure 2.5 lies below the blue line. This result is consistent with the findings by Burkart et al. (2003) and Bhattacharya and Ravikumar (1997), where family firms are more likely to hire an external manager if either the difference in managerial talent between the owner and the external manager is too high, or the project quality is high.

The higher costs force the project owners to hire an external manager, only if the generated surplus is enough to cover the outside options of both parties and the cost of hiring. This means that now the share of project owners who choose to leave the project idle or

Table 2.6: Key model statistics: Benchmark vs. high costs of hiring

Statistic	$\kappa = 4.5$	$\kappa = 10$
Firm Share	1.13%	0.41%
Family Firm Share	31.43%	98.3%
Relative Family Firm Size	0.73	0.50
Output Share of Fam Firms	22.8%	47.9%
Normalized TFP	100 %	89.7 %

Note: The family firm share in the model is defined as the number of firms managed by the project owners divided by the number of all firms. Relative family firm size is the ratio of the average number of employees in the family firms and the average number in the firms with external managers.

manage it themselves is higher, and the demand for external managers declines. Table 2.6 compares several important moments in the two steady states.

We can see from the table that the increase in the hiring cost affects both the number of firms in the economy and the share of owner (family) managed firms. The number of firms declines by more than 2.5 times. This is because many project owners leave their projects idle as, given the high cost of hiring, it is not optimal for them to hire an external manager, and their managerial talents do not allow them to operate the firms themselves. On the other hand, from those who become firm owners, 98 percent choose to manage the firms themselves, in comparison, only 31.4 percent of firm owners manage their own projects in the benchmark economy. The consequent concentration of firm ownership and management leads to misallocation of managerial talent. This is because the majority of firms now are managed by the less talented owners, while a significant share of highly talented potential managers either supply their labor in the labor market, or operate projects of lower quality. The relative family firm size, defined as the ratio of the average size of firms managed by the owner and the average size of firms managed by external managers, declines from 0.73 to 0.5. This result is in line with the findings by Burkart et al. (2003) and Bloom and Van Reenen (2007), that family firms are smaller on average, and even more so in the developing countries. Lastly, the misallocation of managerial talent affects the economy level TFP, which declines by more than 10 percent.

2.6.1 Cross-Country Analysis

In this section, I use the model to study the role of managerial talent misallocation in explaining the cross-country differences in measured TFP.

The cost of hiring κ affects the decisions of the project owners to hire an external manager, therefore it governs the share of family managed firms in the model economy. I vary κ such

Table 2.7: The share of family managed firms in the universe of medium sized manufacturing firms versus TFP relative to the US for a set of countries.

Country	Share Family Managed	TFP/TFP_{US}
Argentina	48%	0.604
Brazil	60%	0.465
Chile	38%	0.594
China	29%	0.220
Greece	55%	0.603
India	70%	0.245
Italy	57%	0.849
Mexico	45%	0.481
US	20%	1.0

Sources: WMS years 2004-2010 & UNIDO World Productivity Database, year 2000. The share of family managed firms is for the universe of manufacturing firms with larger than 100 employees. The country level TFP is relative to the US.

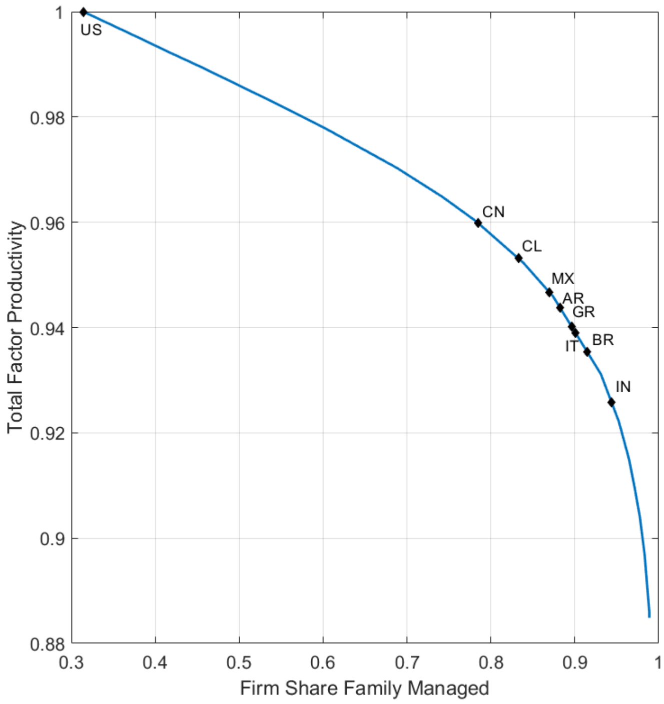
that in the model equilibrium the share of firms managed by owners is equal to the shares of family managed firms observed in a list of countries[10] (see table 2.7). Next, for each country I calculate the model implied decline in the TFP due to the increase in the share of family managed firms, and compare it to the actual measured TFP difference between that country and the US.

The model predicted relationship between TFP and the measure of firm ownership and management concentration is plotted in Figure 2.6. The points in the graph represent the model predicted drop in the TFP for the benchmark economy, if the share of family managed firms was increased to the levels observed in the respective countries.

As expected, the higher is the share of firm ownership and management concentration in a given economy, the higher will the model implied misallocation in managerial talents be, leading to a drop in the TFP. It is particularly interesting to note that the relationship between the two is concave. This means that the gains from improving the conditions for family firms to hire external managers in developing countries such as India and Brazil will be higher than in developed countries. This is because in the model a small decline in initially very high costs of hiring first benefits the owners of high quality projects, and especially those with low managerial talents. The decline in the cost makes it possible for them to hire external managers from the top percentiles of talent distribution, who previously supplied

[10] I use the World Management Survey database to calculate the share of family managed firms in each country. Since the database provides information only on manufacturing firms with between 100 and 5.000 employees, I compare the data with the share of family managed firms only for firms with more than 100 employees in the model.

Figure 2.6: Model implied relationship between the share of family managed firms in the medium sized firm population and the TFP



The share family managed is the equilibrium share of firms managed by the owners within all firms in the model. The TFP of the countries are expressed relative to the TFP of the benchmark model.

their labor in the labor market due to the lack of demand for managerial positions. This alleviates the talent misallocation both on the extensive (occupational choice) and intensive (assortative matching) margins, and has the strongest effect on TFP.

Lastly, table 2.8 presents the share of country TFP differences relative to US that can be explained by the talent misallocation channel.

For most of the countries in the list, the proposed mechanism explains from 10% to 15% of the total factor productivity difference from the US level. China and Italy are the outliers. The model explains only 5% of the TFP difference for China. The low explanatory power of the model for China can be due to the fact, that a large share of Chinese firms are state-owned. Even though these firms perform badly on average (e.g. Zhang et al., 2003; Driffield and Du, 2007) presumably due to bad management (Bloom and Van Reenen, 2010), the model concentrates only on family firms as a source of managerial talent misallocation, and therefore explains only a small share of difference in measured TFP. For Italy the managerial talent misallocation channel can solely explain around 40% of the TFP difference from the US. This is mainly because Italy is the only developed country in the list, and the TFP difference between Italy and the US is small.

Overall, the cross-country analysis shows that the proposed mechanism can explain a

Table 2.8: The share of TFP difference from the US, explained by the model, for a set of developing and developed countries

Country	Family Share	TFP/TFP_{US}		Share Explained
		Data	Model	
Italy	57%	84.9%	93.9%	39.8%
Greece	55%	60.3%	94.1%	15.1%
Argentina	48%	60.4%	94.4%	14.1%
Brazil	60%	46.5%	93.5%	12.1%
Chile	38%	59.4%	95.3%	11.6%
Mexico	45%	48.1%	94.7%	10.2%
India	70%	24.5%	92.6%	9.8%
China	29%	22.0%	95.8%	5.1%

Sources: WMS years 2004-2010 & UNIDO World Productivity Database, year 2000. The share of family managed firms (Family Share) is for the universe of manufacturing firms with larger than 100 employees. The country level TFP values are relative to the US both in the data and in the model.

significant part of the cross-country differences in total factor productivity. This implies that better understanding the costs firm owners face when hiring external managers in developing countries should be a priority, as it can help to develop targeted policies to mitigate these costs and lead to improvements in firm productivity. The model estimated TFP losses are only the lower bound, as they don't capture the potential dynamic effects of firm ownership and management concentration. In particular, in a framework with endogenous human capital accumulation, the high hiring costs will increase job security for family managers, decreasing the incentives for them to invest in their human capital. Similarly, individuals with no project and with high managerial talent will also make sub-optimal investment decisions due to lower demand for managerial positions and lower wages.

2.7 Conclusion

In this chapter, I document a negative correlation between the share of individual owned firms in a country and its development level. I further show that in developing countries a larger share of these firms are managed either by the owners or by their relatives. Based on the empirical results that insider managed firms perform poorly relative to firms managed by professional managers, I argue that the high firm ownership and management concentration in developing countries can be a source of sizeable misallocation of managerial talent and thus, it can explain a significant part of cross-country differences in measured TFP.

To study the importance of the proposed mechanism, I develop a small-open economy model of occupational choice, where agents have heterogeneous managerial talents and some share of them are endowed with projects of varying quality. The combination of projects and managerial talents creates a firm with Lucas span-of control technology and productivity, which is a function of the combined talent and project qualities. Project owners can choose either to manage the projects themselves or to hire an external manager and pay a hiring cost. I augment the differential rents mechanism by Sattinger (1979) to allow for heterogeneous outside options, and embed it into the model of occupational choice. The hiring cost affects the decision of project owners to hire external managers and thus, the share of owner (family) managed firms in the economy and the level of managerial talent misallocation.

I calibrate the model to match several moments of empirical distributions of firm size and managerial compensation, and the concentration of firm ownership and management in the US manufacturing industry. In the counter-factual analysis, an increase in the hiring cost raises the share of owner (family) managed firms in the economy, the firm share in total population and the relative size of family firms decline, consistent with the results in the literature. The model predictions show that the channel of managerial talent misallocation solely can explain from 10 to almost 15 percent of cross-country differences in TFP and around 40% of the difference in measured TFP between Italy and the US.

Chapter 3

Occupational Choice, Social Insurance and Endogenous Financial Constraints

3.1 Introduction

Access to finance has been shown to be a significant obstacle for entrepreneurial start-ups and investment decisions especially in developing countries in the empirical literature (e.g Banerjee and Duflo, 2005; Levine, 2005). Many authors (Buera et al., 2011; Midrigan and Xu, 2014, among others) have studied the quantitative effects of financial frictions on per capita income, total factor productivity and firm dynamics through resource misallocation and entrepreneurial entry distortions. But very few have addressed the core reasons behind differences in severity of financial frictions in some countries relative to others, mostly attributing these differences to cross-country variations in institutional development.

In this paper, I show that financial frictions can arise endogenously under limited commitment if, due to asymmetric information, the lenders (banks, other financial intermediaries) cannot perfectly distinguish between entrepreneurial types and therefore, riskiness of entrepreneurs. The social policies can further exacerbate or mitigate the financial frictions through their effect on the outside options of high risk, marginal entrepreneurs, and thereby, on the occupational distribution and the composition of entrepreneurs in the economy. In particular, if social benefits provided by the government are low, in order to generate enough income for subsistence the unemployed will be forced to switch to entrepreneurship instead of searching for a job. This will deteriorate the composition of entrepreneurs in the economy. As a consequence, the lenders will charge higher borrowing interest rates in response to higher riskiness of lending due to asymmetric information. The efficiency loss arises from two channels. First, through misallocation of capital and distortions in entry and technology adoption because of higher borrowing interest rates, and second, through misallocation of labor, as the unemployed are forced to spend less time on job search. This efficiency loss translates into lower per capita output and output-to-labor ratio. Increasing the social benefits will have the opposite effect.

The Schumpeterian view of entrepreneurs as innovators and a source of creative destruction was dominant in the economic literature until recently. The entrepreneurs were mostly viewed as those with innovative ideas and superior abilities to operate a business, who had large potential of creating new jobs and developing innovative technologies. But with the availability of new data sources it became clear that a significant share of individuals become entrepreneurs out of necessity (subsistence entrepreneurs). This is especially true for the developing countries (e.g Schoar, 2010; Ardagna and Lusardi, 2010). In contrast to opportunity entrepreneurs, the subsistence entrepreneurs choose the entrepreneurial occupation only because of the unavailability of paid employment. The composition of entrepreneurs varies across countries, with the share of subsistence entrepreneurs increasing with the entrepreneurship rate. This means that the marginal entrepreneurs in developing countries are subsistence, with low outside options of entrepreneurship. Hence, differentiating between these two types of entrepreneurs is important to understand cross-country differences in firm distribution, entrepreneurship shares etc. In this paper, I additionally show that, first, social insurance has differential effects on the decision to become a subsistence or an opportunity entrepreneur, thereby it alters the composition of entrepreneurs in the economy, and second, that the composition of entrepreneurs is also important to explain the cross-country variation in access to finance for SMEs and output-to-labor ratios. I argue that this is particularly the case in the context of developing economies, given that developing economies are characterized with low social insurance, high shares of small scale entrepreneurs (e.g. Gollin, 2002; Poschke, 2018a), and severe access to finance for SMEs.

I develop a quantitative model of occupational choice that incorporates the proposed mechanism, and I use it for the cross-country quantitative analysis of the role of social policies. In the model, the infinitely lived heterogeneous agents choose between working in the labor market, staying unemployed, and becoming an entrepreneur. The unemployed receive social benefits financed from a lump-sum tax. The entrepreneurs can operate either in the traditional or in the modern sectors. They gain access to production technology, which is more productive in the modern sector, but to operate there they have to pay an entry cost. Modelling a two-sector economy allows for studying the effects of financial constraints on technology adoption. The financial market suffers from limited commitment, and production shocks can force the entrepreneurs to default on their debt, which means that the borrowing rates contain risk premia. Another important feature of the model is that the lenders cannot perfectly observe the types of the entrepreneurs that borrow. Only the amount the entrepreneurs borrow and the sector they operate in are observed. This set up of the information structure allows for existence of pooling equilibria in the capital market (e.g. Athreya et al., 2012) and links the composition of entrepreneurs in the economy to the access to finance for SMEs[1].

The model allows for classifying the entrepreneurs into subsistence and opportunity groups, given their endogenous motivations for the occupational choice. Consistent with the definitions used in the data, I define an entrepreneur to be subsistence, if she satisfies one of the following conditions: Her value function as an employed is higher than that as an entrepreneur, but she doesn't have a job offer, or her value function as an entrepreneur is higher than that as unemployed, and the latter is higher than her value function as employed. The entrepreneurs are classified as opportunity, if their value function as an entrepreneur is higher than that as an employee, and the latter is higher than their value function as unemployed. This means, that on average the subsistence entrepreneurs have lower entrepreneurial talent and/or are more likely to face a production shock relative to opportunity entrepreneurs, and thus, they are more likely to default on their loans. I show that while the share of subsistence entrepreneurs in the model is negatively related to the social benefit, the relation between the share of opportunity entrepreneurs and the social benefit is non-negative. Therefore, if the social benefit is low, the share of subsistence entrepreneurs in the economy increases, as a larger share of unemployed become entrepreneurs. This affects the quality of the pool of entrepreneurs and increases the riskiness of lending, driving the borrowing interest rates up. But the tightening of the borrowing constraint forces the opportunity entrepreneurs to make sub-optimal investments, and it negatively affects the asset accumulation of the opportunity entrepreneurs and their transition to the more productive sector. Furthermore, as more unemployed transition to entrepreneurship because of the low social benefit, they do not receive job opportunities, which leads to misallocation of labor resources and to a decline in employment rate as observed in the data.

I then calibrate the model to match several empirical moments of the US firm distribution, access to finance for SMEs and the labor market. The model does well in hitting the targeted data moments and captures such non-targeted moments as the investment-to-output ratio and wealth distribution. I then use the model to study the quantitative importance of the social benefit in explaining cross-country differences in the occupational distribution, firm distribution, access to finance and output-to-labor ratio. I concentrate the counter-

[1]The assumption of unobservable entrepreneurial types is motivated by the large literature on the opaqueness of small and medium enterprises for banks (see e.g. Petersen and Rajan, 1994).

factual analysis on the economy of Chile. The choice of Chile is motivated by the fact that within the OECD member countries, it has one of the highest entrepreneurship rates, and is relatively less developed. Additionally, the data availability both on the individual and macro levels is another important factor. Using the 2015 National Socio-economic Characterization Survey, I calculate the average social benefit the unemployed receive in Chile and feed this value in the model. The model predicts 20% entrepreneurship rate and 63% employment rate, very close to the 20.5% entrepreneurship and 66.9% employment rates observed in the data for Chile. The rise in the entrepreneurship rate is mainly due to the entry of the subsistence entrepreneurs. The model predicted borrowing interest rate spread for SMEs is around 55% of the borrowing rate spread in Chile, which naturally is accompanied by a decline in investments especially by SMEs in the economy. The model can explain 15.8% of the difference in output-to-labor ratio between Chile and the US. Furthermore, the model predicts a higher share of small firms in Chile relative to the US, consistent with the data.

I document several cross-country facts that are consistent with the proposed mechanism. I first use the Global Entrepreneurship Monitor (GEM) database to show that the share of subsistence entrepreneurs in total entrepreneurship is higher in developing countries and is increasing with the entrepreneurship rate across countries. The GEM database is useful for this analysis, as it provides information on the reasons behind individuals' choices to become entrepreneurs. Next, I show that the cross-country borrowing interest rate spread for small and medium firms relative to large firms is positively correlated with entrepreneurship rate, which, combined with the first result, provides empirical evidence for the proposed mechanism. Then, I use the OECD database on cross-country unemployment insurance (UI) policies to provide evidence, that the share of entrepreneurs in an economy is negatively correlated with country level replacement rate of unemployment. I turn to the US Current Population Survey (CPS) to further analyse the response of unemployed to changes in the UI policy on the individual level. Using the variations in the UI eligibility period across time and states in the US during Great Recession[2], I find that a temporary increase in the eligibility period for unemployment benefits leads to a decrease in the likelihood of becoming an entrepreneur for the unemployed, relative to employed and non-employed[3]. This finding further validates the idea that social policies are important for the decision to become an entrepreneur, especially for the unemployed, and that social policies can generate aggregate

[2]In the scope of Extended Benefit (EB) and Emergency Unemployment Compensation (EUC) programs, the maximum unemployment insurance eligibility periods where extended from 26 weeks to 99 weeks in several US states for certain periods of time during Great Recession.

[3]Similar to Fairlie and Fossen (2018), in this analysis I think of individuals who become entrepreneurs out of unemployment as subsistence entrepreneurs, while those who transition to entrepreneurship from employment are considered as entrepreneurs pursuing an opportunity.

general equilibrium effects through the occupational choice channel. Finally, to motivate the assumption of information asymmetry between the lenders and the entrepreneurs in the mechanism, I use individual level data of entrepreneurs in Mexico to show, that there is large overlap in the asset, educational and industry distributions of opportunity and subsistence entrepreneurs. This implies that observationally these two groups of entrepreneurs are similar.

My work is related to several strands of literature. First, it relates to the macroeconomics literature on financial frictions and development. See, for example, the pioneering papers by Amaral and Quintin (2010), Jeong and Townsend (2007) and Greenwood et al. (2010). Buera et al. (2015) present a comprehensive overview of the literature. Midrigan and Xu (2014) find that collateral constraints have sizable effects on entrepreneurial entry and technology adaption, which translate to lower TFP. In contrast, Buera et al. (2011) show that capital misallocation across firms resulting from financial frictions is more sizable. Their model predicts small average firm size in developing economies found in the data. Allub and Erosa (2014) find similar results using data on Brazil. Relative to the papers in the literature, financial frictions in my model depend on the composition of entrepreneurs in the economy. This allows for explaining the positive correlation between entrepreneurship rates and access to finance across countries, worse access to finance for small versus large firms observed in the data, and for studying the role of labor market policies on resource allocation and growth.

Donovan et al. (2018) study the labor market churn in a group of countries. They show that in developing countries people who were previously inactive[4], are much more likely to become self-employed relative to finding a wage work, than in the developed countries. Their findings provide further support for the view that self-employment is a substitute to unemployment and missing social assistance in developing countries. Poschke (2013) studies the motivations for becoming an entrepreneur and the effects of labor market policies. In another paper, Poschke (2018b) argues that the labor market frictions can explain a significant part of cross-country differences in occupational distribution. In my model, the level of social insurance is the opportunity cost of becoming a subsistence entrepreneur for the unemployed, hence, it affects the occupational distribution. Furthermore, the subsistence entrepreneurs have negative externalities on opprtunity entrepreneurs, as their entry affects the borrowing interest rates, similar to theoretical models of Ghatak et al. (2007) and Scheuer (2013). This means that in my model social policies can be welfare enhancing

[4]In their database, Donovan et al. (2018) group people into being employed, unemployed or inactive (not employed) consistent with the definitions used in the CPS.

not only for the subsistence entrepreneurs, but also for the opportunity entrepreneurs, by relaxing access to credit for them.

Lastly, my work also relates to the micro-finance literature. My modeling of two types of entrepreneurs is consistent with the results of Banerjee et al. (2018), Karaivanov and Yindok (2016), Angelucci et al. (2015), who find differential effects of micro-finance on different types of entrepreneurs. Banerjee et al. (2018) use the time of business creation as a method to separate between the 'Gung-ho' and 'Reluctant' entrepreneurs in the data, while Karaivanov and Yindok (2016) use a structural model to separate the 'voluntary' and 'involuntary' entrepreneurs [5].

The remainder of the chapter is organized as follows. In section 3.2, I discuss several cross-country stylized facts that bring empirical evidence to the propose mechanism. Section 3.3 presents the quantitative model. In section 3.4, I describe the calibration procedure and present the implications of the benchmark model. In section 3.5, I run counter-factual analyses and study the model predicted outcomes for Chile. Section 3.6 concludes.

3.2 Empirical Facts

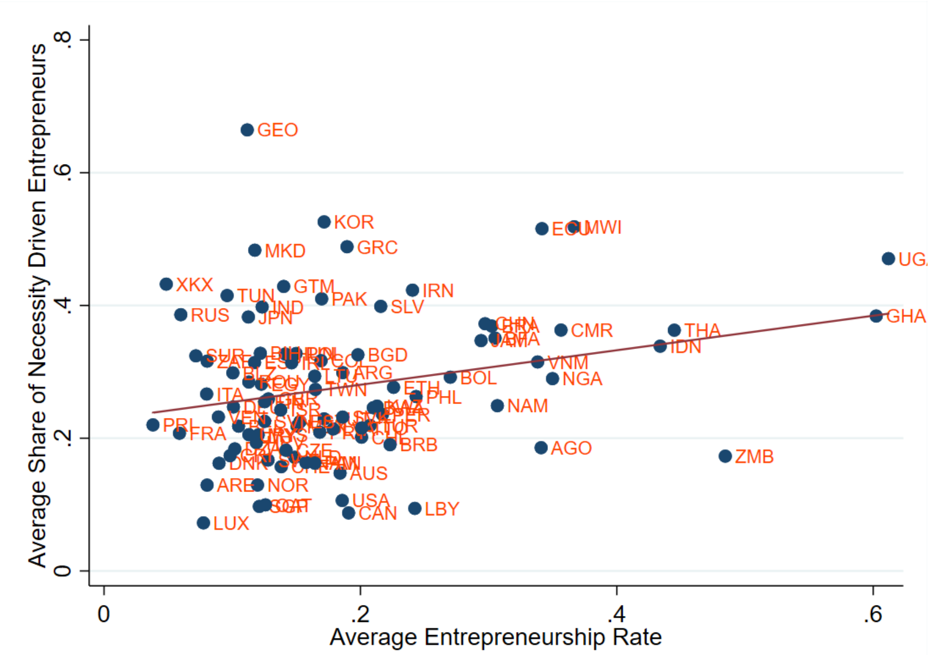
3.2.1 Cross-country Analysis

In this section, I present several cross-country facts on the relation of entrepreneurship rate with access to finance and unemployment insurance (UI) policies that support the proposed mechanism. Additionally, I conduct an individual level analysis to study the effects of unemployment benefit extension policies on the likelihood to become an entrepreneur in the US. I show that the increase in the unemployment benefit eligibility period in several US states during Great Recession led to a decline in the likelihood for the unemployed to become entrepreneurs, relative to the employed and non-employed. This result is consistent with the hypothesis that social policies play an important role in occupational decisions.

I use the Global Entrepreneurship Monitor (GEM) Adult Population Survey as the main source of analysis, to study cross-country differences in the share of subsistence entrepreneurs. The GEM database is a combination of harmonized population surveys for a wide range of countries. It includes data on more than 100 countries for the period from 1999 to 2014. A unique feature of the database, that makes it especially useful for the current analysis, is that the surveys ask participants specifically for the reasons they became entrepreneurs. In particular, an individual is defined as an entrepreneur if her answer to the

[5] The so-called 'Reluctant' entrepreneurs in Banerjee et al. (2018) and the 'involuntary' entrepreneurs in Karaivanov and Yindok (2016) are comparable with the definition of subsistence entrepreneurs I use in the paper.

Figure 3.1: The share of necessity-driven entrepreneurs versus average entrepreneurship rate across countries



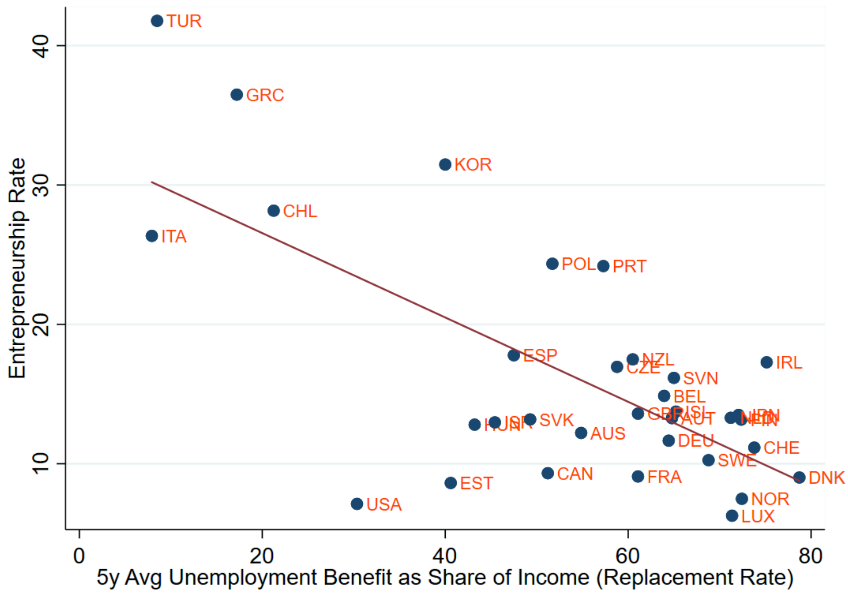
Sources: GEM Adult Population Survey. The regression coefficient is 0.26 with a p-value of 0.015. The share of necessity driven entrepreneurs is defined as the share of people within all entrepreneurs, who say they became entrepreneurs because they had no better choices for work. Each data point represents the average value for a given country within 2010-2014 period.

survey question "Are you, alone or with others, currently the owner of a company you help manage, self-employed, or sell any goods or services to others?" is "Yes". The entrepreneurs who specify that they chose the occupation because they had no better choices for work are defined as necessity driven entrepreneurs[6], which coincides with the definition of subsistence entrepreneurship in the literature. I use this information to calculate the share of necessity driven entrepreneurs in the population of entrepreneurs for each country. I plot the average share of necessity driven entrepreneurs by country in figure 3.1, versus the average entrepreneurship rate on the horizontal axis. The relationship is statistically significant with an OLS regression coefficient of 0.26 and p-value of 0.015.

Figure 3.1 shows that in countries with high entrepreneurship rates, the share of entrepreneurs identifying as subsistence is also high. This means that the difference in entrepreneurship rates across countries is mainly due to the entry of marginal entrepreneurs who make the occupational decision out of necessity. In the Appendix Figure B.3, I also show that the share of subsistence entrepreneurs in total entrepreneurship is highly

[6]The survey question used for identifying the necessity driven entrepreneurs in the GEM questionnaires is as follows: "Are you involved in this firm to take advantage of a business opportunity or because you have no better choices for work?". The following answers are possible: (i) take advantage of a business opportunity, (ii) no better choices for work, (iii) have a job but seek better opportunities, (iv) other. I define the entrepreneurs to be necessity driven if their answer is either (ii) or (iii).

Figure 3.2: Entrepreneurship rate versus 5 year average net replacement rate for unemployment



Source: OECD database. Each data point represents the average for years 2001-2014 for a given country. The entrepreneurship rate is defined as the number of entrepreneurs divided by country labor force. The regression coefficient is -0.26 with p-value less than 0.01.

correlated with country development, measured by real GDP per capita. One can observe that while in countries with developed social insurance systems like Norway, Sweden or Denmark the share of subsistence entrepreneurs in total entrepreneurship is only around 15 percent, it is around 45-50 percent in Pakistan and Uganda.

A key part of the proposed mechanism is that the entrepreneurship rate is sensitive to the social insurance provided by the government. This is because the social insurance is the opportunity cost of becoming an entrepreneur for the subsistence entrepreneurs. To see whether this relationship can be observed in the data, I turn to the OECD database. The OECD database provides aggregate data both on entrepreneurship rate for OECD countries and the 5-year replacement rate of unemployment benefit, which I use as a proxy for social insurance. Ideally, for this analysis one would need data on the level of social insurance and the share of subsistence entrepreneurs in a group of countries. Unfortunately, harmonized data on government provided social insurance across countries doesn't exist. Additionally, the OECD database doesn't differentiate between subsistence and opportunity entrepreneurship, and the databases of OECD and GEM have a small overlap. This is why I present the relation between the replacement rate of unemployment benefit and entrepreneurship rate instead. Appendix Figure B.4 plots the relationship between necessity driven entrepreneurship rate and UI level for the set of OECD countries that is overlapping with GEM database. These relationships are very similar. Both the entrepreneurship rate

Table 3.1: The effect of 5 year average net replacement rate of unemployment on entrepreneurship rate

Dependent variable: *entrepreneurship rate*

	(1)	(2)	(3)	(4)
ubenefit	-0.26^{***}	-0.27^{***}	-0.02	-0.057^{***}
R^2	0.39	0.4	0.97	0.35
TD	No	Yes	No	Yes
FE	No	No	Yes	Yes
obs	425	425	425	425

Source: OECD Database, years 2001-2014. The explanatory variable is the 5-year average unemployment benefit as a share of income for a given country. TD - time dummies, FE - fixed effects (country dummies). (*)-p-value< 0.1, (**)-p-value< 0.05, (***)-p-value< 0.01

and the share of necessity driven entrepreneurs are negatively correlated with the replacement rate of unemployment benefit.

The entrepreneurship rate is the share of self-employed in the labor force. In the OECD database, self-employment is defined as the employment[7] of employers, workers who work for themselves, members of producers' co-operatives, and unpaid family workers. Figure 3.2 presents the relationship between the two variables for the period from 2001 to 2014.

The countries covered by the OECD database are mostly developed, and there are no low or low-middle income countries[8] in the database. This means that the countries in the comparison group are relatively homogeneous apart from social policies. I also use the panel dimension of the database to study the within country effects of unemployment benefit. The regression results are presented in Table 3.1.

As expected, the regression results too point to the negative relationship between country-level entrepreneurship rate and unemployment insurance. I estimate the regression with and without time and country fixed effects. In specification (4), I use only the within country variation in the estimation, and still the relationship between social policies and entrepreneurship rate is negative and highly significant. It implies that an increase in the replacement rate of unemployment by 10 percentage points is associated with a decrease in entrepreneurship rate by 0.6 percentage points. Naturally, this result doesn't imply any causal relation between social policies and entrepreneurship rate. I will further address this issue using individual-level data in the next subsection.

[7]The OECD database defines the employed people as those aged 15 or over who report that they have worked in gainful employment for at least one hour in the previous week or who had a job but were absent from work during the reference week.

[8]According to the definition by World Bank

Figure 3.3: Scatter plot of the average share of entrepreneurs in labor force versus the average spread in borrowing rate between SMEs and large firms by country

Source: OECD database, years 2007-2015. The SME borrowing interest rate spread is defined as the difference between the average interest rate for SME loans and the average rate for loans for large firms. See the definition of SME loans in the text. The OLS regression coefficient is 0.048 with p-value < 0.01.

The OECD database also provides data on average borrowing interest rates for small and medium enterprises and large firms in the OECD countries. The data used for the calculation of these rates is mainly based on supply-side data provided by financial institutions, national statistical agencies or central banks. If possible, the database is supplemented by demand side data from regional surveys (OECD, 2017). There is some variation in the definition of SMEs across countries in the database. For the majority of the countries, firms with less than 200-250 employees are considered to be SMEs. Other countries consider a firm to be an SME if its turnover within a year is less than a given threshold. There is also some variation in the definitions of small and medium business loans. Generally, business loans of amount lower than a given country specific threshold and with a duration of one year are considered SME loans[9]. Additionally, the database provides data on country level borrowing interest rate spreads between SMEs and large firms. These spreads are defined as the difference between the average interest rate for SMEs and the average interest rate for the loans taken by large firms. I use this data to show, that the borrowing interest rate spreads[10] for small

[9]E.g. for the European countries this threshold is 1 million Euro. The threshold for Australia and Chile is 1,2 million and 0.63 million Euro respectively.

[10]I use the borrowing rate spreads instead of actual borrowing rates for SMEs in the analysis, in order to control for country specific effects, such as the macroeconomic condition of the country, and the specificities of the interest rate calculations.

Table 3.2: The relationship between the entrepreneurship rate and the borrowing interest rate spread between SMEs and large firms across countries

Dependent Variable: *spread*

	(1)	(2)	(3)	(4)
$semp$	0.048^{***}	0.052^{***}	0.019	0.195^{*}
$lgdp$	-1.51^{***}	-1.45^{***}	-3.43^{***}	-5.06^{**}
$const$	16.67^{***}	15.5^{***}	36.7^{***}	51.1^{**}
R^2	0.378	0.370	0.374	0.351
TE	No	Yes	Yes	Yes
FE	No	No	Yes	Yes
obs	219	219	219	157

Source: OECD database, years 2007-2015. The dependent variable is the difference between the average borrowing interest rates for SME loans and loans for large firms. See the definition of SME loans in the text. *semp*-entrepreneurship rate, *lgdp* - logarithm of country level GDP per capita in constant prices, *const*-the regression intercept, TE - time fixed effects, FE - country fixed effects. Specification (4) uses data for the post-Crisis period, 2010-2015. (*)-p-value< 0.1, (**)-p-value< 0.05, (***)-p-value< 0.01

and medium businesses are higher in countries with high entrepreneurship rates, consistent with the proposed theory[11].

Figure 3.3 presents the cross-country relationship between the borrowing interest rate spread for small and medium businesses and the share of entrepreneurs in the labor force. The data is available only for the years 2007-2015. The two data series are highly positively correlated (with a correlation coefficient 0.54) which serves as evidence for the proposed mechanism. I also control for country development level to study the conditional correlation of the two series. Table 3.2 summarizes the results of the following regression:

$$spread_{it} = \beta_0 + \beta_1 semp_{it} + \beta_2 lgdp_{it} + \delta_t + \gamma_i + u_{it}$$

where $spread_{it}$ is the borrowing rate spread for country i in year t, $lgdp$ is the logarithm of real per capita GDP, δ and γ are time and country fixed effects.

As expected, the coefficient on $lgdp$ is negative in all specifications, in line with findings in the empirical literature that borrowing interest rates small and medium businesses face in developed countries are lower in comparison to developing countries (e.g Banerjee and Duflo, 2005). In all specifications except for specification (3), the coefficient on the entrepreneurship rate is positive and significant, which implies that an increase in the entrepreneurship rate in a given country is associated with higher average borrowing rate small and medium

[11] Additionally, Banerjee and Duflo (2005) review the literature on the price of capital in poor countries and find, that borrowing rates for small entrepreneurs can reach to as high as 40%

businesses face, in line with the proposed mechanism. Crawford et al. (2015) study a similar question, using micro-level data on Italian small and medium firms and banks. They find that in most cases an increase in adverse selection from the firm side is associated with higher equilibrium borrowing interest rates. Hertzel and Officer (2012) find that a default of another firm in the same industry is associated with an increase in the borrowing rate a given firm is charged by the banks. They explain their finding with the fact, that banks cannot fully observe firm characteristics and they update their information on the firm's likelihood to default based on aggregate observables.

Additionally, to study the observational differences and financial market behaviour of subsistence versus opportunity entrepreneurs, I use the 2012 National Survey of Mexican Micro-enterprises (ENAMIN). The unit of analysis in the survey are the micro-enterprises with at most ten employees (15 employees for manufacturing firms). The survey covers information both on the individual characteristics of the owners, such as education, age and the reasons for starting a firm, and on the firm characteristics, such as the industry and some balance sheet information. The survey questionnaires include a question that asks why the owners started a firm. I classify the owner as subsistence, if his/her answer was one of the following: (i) 'This was the only way to earn income', (ii) 'The jobs I found were poorly paid', (iii) 'I didn't have other job opportunities'. I compare the educational, industry and asset distributions of the subsistence entrepreneurs to that of the opportunity entrepreneurs in Appendix B. One can see that the distributions have a large overlap. The opportunity entrepreneurs are a bit better educated (Figure B.8) and their asset distribution has fatter right tail (Figure B.7), but industry distributions are similar. The financial market behaviour does not vary much as well. Figure B.10 illustrates the results. A higher share of opportunity entrepreneurs apply and receive credit, while the share of subsistence entrepreneurs who do not apply because they are afraid to be rejected is higher, relative to the opportunity entrepreneurs. I use another method to identify the subsistence entrepreneurs through their answers to why they left their previous jobs[12], and the results are similar.

3.2.2 An Individual Level Analysis for the US

In this subsection, I use the variation in the unemployment benefit eligibility periods in the US during Great Recession to study the role of unemployment insurance on the choice to become an entrepreneur.

[12]Firm owners who said they were fired from the previous job, or their firm was allocated to another town, or because their contract had expired, are identified as subsistence. One issue with this identification method is that a large share of the firm owners didn't have a job previously, so they cannot be classified using this method.

Several social programs were implemented by the US Federal government to decrease the adverse effects of persistent high unemployment rates during Great Recession. The Extended Benefit program was one of them. In the scope of this program and the Emergency Unemployment Compensation (EUC) program, the eligibility period for unemployment benefit in a given state increases automatically, if the three-month moving average unemployment rate in that state is higher than a threshold level. Thus, if in normal times the unemployment eligibility period in the median state is 26 weeks (Chodorow-Reich and Karabarbounis, 2016; Nakajima, 2012), it could reach up to 99 weeks in some states for a limited period of time during the recession, if the programs were triggered.

The unemployment benefit (UB) eligibility period extensions were triggered multiple times in different states during Great Recession. I use this state-time variation in UB eligibility periods to study the effects of the extended benefits on the decision of the employed, unemployed and not-employed population to start a business. I study the following hypotheses: (i) given that the outside options to become an entrepreneur for the unemployed and the employed are the UB and the market wage respectively, all other things equal, the unemployed will be more likely to become entrepreneurs[13], (ii) the increase in the UB eligibility periods during the periods when the programs were implemented made the unemployed less likely to become entrepreneurs, by increasing the opportunity cost of entrepreneurship, while the effects on the employed and not-employed were smaller in magnitude.

I collect the data on state-level implementations of UB extension programs from the web page of the US Department of Labor. I convert the weekly data into monthly and match it with the IPUMS-CPS database for the period from 2003 to 2015. The IPUMS-CPS is based on monthly household surveys that are representative of the entire country. Its rolling panel structure allows the user to track individuals for several months. It includes data on individual characteristics, such as occupation[14], age, education, sex and race. I use only the working age population (age between 18 and 65) for the analysis. Individuals who are at school, in the armed forces or incapable of work are dropped out of the sample.

The panel structure of the database allows me to identify the occupational transitions between employment (wage work), entrepreneurship, unemployment and non-employment. Hence, I am able to study the effects of UB eligibility period extensions on the likelihood of becoming an entrepreneur for the unemployed, relative to the effects on the likelihood for

[13]Most of the unemployed who switch to entrepreneurship naturally will do so due to the absence of other options to earn income for living, which is the definition of subsistence entrepreneurs.

[14]Those who state they worked for pay or profit during the previous week or they worked at least for 15 hours without pay in a family business or farm are considered as employed. Individuals who didn't work the previous week but state they have a job, but were temporarily absent, are also considered as employed. Those in the labor force, not included in the first two groups can further be divided into the subgroups of unemployed and not-employed. People who state they have been searching for a job during the last four weeks, are considered as unemployed, the others are labelled as not-employed

Table 3.3: The effects of the unemployment insurance extensions on the likelihood of becoming an entrepreneur

Dependent variable: *swchsemp*

	(1)	(2)	(3)	(4)
$unemp_{t-1}$	0.012^{***}	0.011^{***}	0.0024^{***}	0.002^{***}
$nonemp_{t-1}$	0.016^{***}	0.016^{***}	-	-
emp_{t-1}	-	-	-0.0094^{***}	-0.009^{***}
$treat$	0.0004^{***}	0.0001	-0.0007^{***}	-0.0004^{**}
$treat \times unemp_{t-1}$	-0.0025^{***}	-0.0016^{***}	-0.0014^{***}	-0.001^{***}
$treat \times nonemp_{t-1}$	-0.0012^{***}	-0.0009^{***}	-	-
$treat \times emp_{t-1}$	-	-	0.0012^{***}	0.0006^{***}
R^2	0.0041	0.004	0.003	0.003
FE	Yes	Yes	Yes	Yes
TFE	Yes	Yes	Yes	Yes
obs	$10,785,335$	$6,558,319$	$10,785,335$	$6,558,319$

Data: IPUMS CPS. *swchsemp* equals to one if an individual becomes an entrepreneur at period t, and zero otherwise. $unemp_{t-1}$, $nonemp_{t-1}$ and emp_{t-1} take the value of one if an individual was unemployed, not-employed or employed respectively during the previous period. *treat* - a dummy variable that is equal to one if the UI eligibility period is extended. In columns (1) and (2), the base occupation is the employed, and the data for periods 2003-15 & 2008-15 is used respectively. Columns (3) & (4) present the results for the specifications where the base occupation is the not-employed, and the data for periods 2003-15 & 2008-15 is used respectively. Month, year and state dummies are included in all specifications. (*) - p-value<0.1, (**) - p-value<0.05, (***) - p-value<0.01.

the employed and not-employed. I estimate the following linear probability equation:

$$\begin{aligned} y_{ist} = c + \beta' X_{ist} + \gamma_u unemp_{ist-1} + \gamma_n EN_{ist-1} + \delta_1 treat_{st} \\ + \delta_2 treat_{st} \times unemp_{ist-1} + \delta_3 treat_{st} \times EN_{ist-1} + \psi' T_t + \phi' S_s + \epsilon_{ist} \end{aligned} \quad (3.1)$$

where y_{ist} equals to one if individual i, living in state s, changes her occupation to entrepreneurship at period t, X_{ist} is a vector of individual characteristics, EN_{ist-1} is equal to either emp_{ist-1} or $nonemp_{ist-1}$, depending on the specification. $unemp_{ist-1}$, $nonemp_{ist-1}$ and emp_{ist-1} are dummy variables that take the value of one if the individual was unemployed, not-employed or employed respectively during the previous period, $treat_{ts}$ is equal to one if the UB eligibility period was extended at period t, in state s, and zero otherwise. T and S are the time and state fixed effects. δ_2 and δ_3 are the parameters of interest. They give the magnitude and the sign of the effect of extended UB eligibility on the likelihood to become an entrepreneur for the unemployed and the not-employed (employed), relative to the employed (not-employed).

One problem with the estimation of equation (3.1) is that the program implementations were not exogenous: they were the responses of the states to the worsening macro conditions and high average unemployment rates. The difference-in-differences approach mitigates the endogeneity bias, especially in the specifications, where the not-employed are the base group. This is because the entrepreneurs who were previously unemployed or not-employed are more likely to be subsistence, and the main difference between the not-employed and unemployed, conditional on observables, is that the former are not eligible for UB, while the latter are eligible.

Table 3.3 summarizes the regression results. The specifications (1) & (3), and (2) & (4) use the data for the periods 2003-2015 and 2008-2015 respectively. The interval 2008-2015 is chosen, because the major share of UB extensions happened during that period. Specifications (1) and (2) use the employed as the comparison group, while the comparison group for specifications (3) and (4) are the not-employed. Month dummies are included in all specifications.

The regression results are in line with the proposed hypotheses. First, the coefficients on the previous period unemployment and not-employment variables are both positive and highly significant in all specifications, indicating that, indeed, the unemployed are more likely to become entrepreneurs relative to the employed. One explanation for this finding could be that the outside options of the unemployed are lower than those of the employed, all other things equal, which makes the choice to become an entrepreneur less costly for the former. Next, the coefficients on the interaction terms for the unemployed are negative and strictly significant, even in the specifications where the comparison group is the not-employed. This result implies that the UB extensions make the unemployed less likely, relative to the employed and not-employed, and also in absolute terms, to become entrepreneurs, consistent with the second hypothesis. I use these results to argue that an increase in social insurance makes the unemployed less likely to switch to entrepreneurship, as it gives them income enough for subsistence. I proceed to the quantitative model in the next section.

3.3 The Model

In this section, I develop a model of occupational choice with endogenous financial constraints that captures the empirical facts discussed in section 3.2. I then use the model to study the role of social policies in occupational choice, access to finance and development.

The model is based on Lucas (1978) occupational choice model with two important extensions. First, the labor market is frictional: Agents can become employed if they receive a job offer. With this extension, agents can choose to become either subsistence or opportunity driven entrepreneurs in the model, and the government provided social benefit serves as the opportunity cost for subsistence entrepreneurs. Second, the capital market suffers from limited commitment from the entrepreneurs, and the entrepreneurs' types are not observable to the lenders. This forces the latter to charge risk premia based on the loan size and the distribution of entrepreneurs in the market. These extensions allow to study the role of the social policy in occupational choice, therefore the entrepreneurship rate, the composition of entrepreneurs, access to finance and output per worker.

3.3.1 Model Setup

The model economy is populated with a unit measure of infinitely lived agents, each of whom is endowed with one unit of labor that she can either supply in the labor market, or use to operate a production technology. Agents maximize the expected value of their life-time utility:

$$
\begin{aligned}
U(c) =& \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{c_t^{1-\sigma}}{1-\sigma} - \mathbb{1}_{(o_t=W)}\kappa \right) \\
s.t. \quad & c_t + a_{t+1} = H_t
\end{aligned}
$$

where c_t and a_{t+1} are the consumption and next period assets, H_t is the end-of-period cash at hand, κ is the disutility from working, and $\mathbb{1}_{(o_t=W)}$ is an indicator function that equals to 1 if the individual is employed in period t.

Agent heterogeneity and occupations. Agents are heterogeneous in four dimensions: (i) their current period assets (a_t), (ii) their job offer status (e_t), (iii) their entrepreneurial talents (z_t), and (iv) the riskiness of operating a production technology (p). The riskiness of operating a production technology (business) is drawn from a continuous distribution $F_p(\cdot)$ for each agent and is a permanent shock. The entrepreneurial talents follow a first-order Markov process: with probability ψ the entrepreneurial talents are re-drawn every period from a continuous distribution $F_z(\cdot)$. Agents who have a job offer ($e_t = 1$) can choose between staying unemployed, being an employee, and becoming an entrepreneur. Those with no offer ($e_t = 0$) do not have the option to become an employee.

Labor market and the social benefits. The labor market is frictional. Similar to Krusell et al. (2011), the employed workers lose their opportunity to be employed in the next period with probability λ, and the unemployed receive a job offer next period with probability $(1 - \mu)$. The entrepreneurs do not receive a job opportunity next period. The employees (wage workers) are compensated with the competitive market wage w_t, and the unemployed receive social benefit b that is financed by a lump sum tax τ. Additionally, agents face disutility κ if they are employed.

Entrepreneurs. Agents who choose to become entrepreneurs can either enter the traditional, or the modern sectors. Those entering the modern sector have access to more productive technology, but they have to pay a fixed cost of entry Θ, financed from own assets. Similar to Allub and Erosa (2014), I assume that entrepreneurs can either hire outside labor or supply some part of their own labor as an input[15]. The production technology is decreasing returns to scale, as in Lucas (1978), and depending on the choice of sector, is given by:

$$y_t = \varphi^{\mathbb{1}_{T=1}}(1 - m_t) z_t k_t^{\alpha} (m_t + l_t)^{\gamma} \tag{3.2}$$

where k_t and l_t are the capital and labor choices respectively, m_t is the share of the entrepreneur's time she chooses to supply as labor input, and $\varphi \in (0, 1]$ is the productivity in the traditional sector relative to the modern sector. $\mathbb{1}_{T=1}$ is an indicator function, that takes the value of one if the entrepreneur operates in the traditional sector, and zero otherwise. The production technology is decreasing returns to scale, meaning that $\alpha + \gamma < 1$. The production process is subject to shock ϵ, drawn from distribution $F_{\epsilon}(\cdot|p)$. This shock is realized after the production process and takes away amount ϵ of the agent's assets. A higher value of p implies that the entrepreneur is more likely to face a production shock[16].

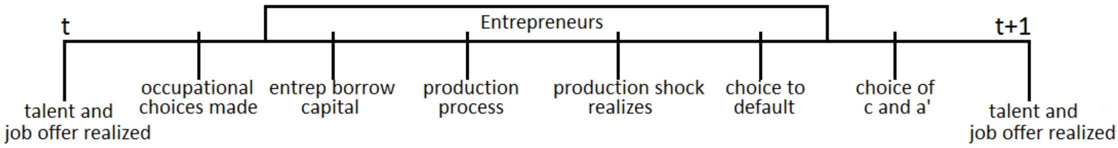
Capital market and default. The entrepreneurs have access to the capital market and they can use the borrowed capital only for production purposes. The market suffers from limited commitment as the entrepreneurs can default on their loans. In case they default, the entrepreneurs lose all their assets and income up to a certain exemption level, given as share ξ of the market wage. I assume that the decision to default only affects an individual's current cash-at-hand, but it doesn't have dynamic effects[17]. The capital market is competitive, where the lenders borrow capital from the world with interest rate $\bar{r}$ and lend it to the entrepreneurs. The lenders cannot observe the state variables of the entrepreneurs. Instead, they observe the amount borrowers ask and the sector they operate in. While the assumption of asymmetric information is backed by the large literature on the opaqueness of SMEs for banks (e.g. Petersen and Rajan, 1994), the assumption of the observability of the sector is motivated by the fact, that the banks can observe the business operation scales

[15]This assumption allows low skilled entrepreneurs to operate a business without hiring external labor, and it is helpful in matching cross-country entrepreneurship rates.

[16]The distribution of ϵ has a mass at 0 and a positive support, additionally $\mathbb{P}(\epsilon = 0|p) = 1 - p$ and $\mathbb{P}(\epsilon > 0|p) = p$.

[17]This assumption is necessary only for computational purposes. Without this assumption, one would need to add an additional state variable to already large state space.

Figure 3.4: The timing of the agents' decisions and the realizations of the shocks



of borrowing firms.

Timing. The timing of the decisions is shown in Figure 2.3. In the beginning of period t, the job offer and the entrepreneurial talent of each individual are realized. Given the state variables, which also include the agent's assets a_t and her type p, each agent chooses her occupation. If an agent enters the modern sector, she has to pay the one-time cost of entry Θ. State variable $g \in \{0, 1\}$ keeps track of whether an agent needs to pay Θ to operate in the modern sector. Next, each entrepreneur chooses the amount to borrow, given the borrowing interest rate schedule $r_t(x_t, J)$. The latter is a function of the sector J where the entrepreneur operates, and her asked amount x_t. After the production process, the production shock is realized and it takes away ϵ amount of the entrepreneur's income. The entrepreneurs then choose whether to pay the debt or to default. This decision determines their cash-at-hand in period t, and in the end of the period all agents make the consumption-savings choice and move to the next period.

3.3.2 Recursive Formulation

I study the implications of the model in the stationary equilibrium. As the policy functions and the aggregate variables are independent of time in the equilibrium, I drop the time index from the recursive formulation. The beginning-of-period value functions for agents who have to pay the fixed cost of entry in order to operate in the modern sector ($g = 0$) are as follows:

$$V_{e=0,g=0}(z, a, p) = \max\{N(z, a, p), \mathbb{E}(T(z, a, p, \epsilon)|p), \mathbb{E}(M_0(z, a, p, \epsilon)|p)\} \tag{3.3}$$

$$V_{e=1,g=0}(z, a, p) = \max\{W(z, a, p), V_{e=0,g=0}(z, a, p)\} \tag{3.4}$$

and for agents who were entrepreneurs in the modern sector during the previous period ($g = 1$), the value functions read:

$$V_{e=0,g=1}(z, a, p) = \max\{N(z, a, p), \mathbb{E}(T(z, a, p, \epsilon)|p), \mathbb{E}(M_1(z, a, p, \epsilon)|p)\} \tag{3.5}$$

$$V_{e=1,g=1}(z, a, p) = \max\{W(z, a, p), V_{e=0,g=1}(z, a, p)\} \tag{3.6}$$

where the first index of the value functions equals to one if the agent has a job offer, and the second index value equals to one if the agent was in the modern sector in the previous period (which means she does not have to pay Θ if she decides to operate in the modern sector). W, N, $\mathbb{E}(T|p)$, and $\mathbb{E}(M_0|p)$ are the value functions of the workers, the unemployed, and the expected value functions of entrepreneurs in the traditional and modern sectors respectively. The value functions of the entrepreneurs are in expected values as they depend on the within-period realizations of the production shock. The index 0 of the value function of the entrepreneur in the modern sector means that she has to pay a fixed cost of entry.

The value functions of the workers and the unemployed are given by:

$$W(z,a,p) = \max_{a',c} \left\{ u(c) - \kappa + \beta \mathbb{E}\left[(1-\lambda)V_{10}(z',a',p) + \lambda V_{00}(z',a',p)\right]\right\} \tag{3.7}$$

$$s.t. \quad c + a' = (1+\bar{r})a + w - \tau$$

$$c \geq 0; \quad a' \geq 0$$

$$N(z,a,p) = \max_{a',c} \left\{ u(c) + \beta \mathbb{E}\left[(1-\mu)V_{10}(z',a',p) + \mu V_{00}(z',a',p)\right]\right\} \tag{3.8}$$

$$s.t. \quad c + a' = (1+\bar{r})a + b - \tau$$

$$c \geq 0; \quad a' \geq 0$$

where w is the wage, b is the social benefit, and τ is a lump sum tax. The value function of the unemployed is increasing in b. This means that, everything else equal, an increase in the social benefit will lead to a larger number of agents who choose to stay unemployed instead of working or becoming an entrepreneur. The value function of the employed is increasing in the wage level.

If an agent becomes an entrepreneur, her value function will depend on her state variables, the realization of the production shock ϵ and her consequent choice of default. ϵ is realized only after the occupational choice and the choice of production inputs, which means that in the beginning of the period the agent knows only its distribution. Given that, the beginning-of-period value function for the entrepreneurs in the traditional sector will be as follows:

$$\mathbb{E}(T(z,a,p,\epsilon)|p) = \sum_{\epsilon} T(z,a,p,\epsilon)\mathbb{P}(\epsilon|p) \tag{3.9}$$

$$T(z, a,p, \epsilon) = \max_{a',c} \{u(c) + \beta \mathbb{E}[V_{00}(z', a', p)]\} \tag{3.10}$$
$$s.t. \quad c + a' = \Pi^T(z, a, \epsilon) - \tau$$
$$\Pi^T(z, a, \epsilon) = \max \left\{\pi^T(z, a) - \varphi\epsilon, \xi w\right\} \tag{3.11}$$

$$c \geq 0; \quad a' \geq 0$$

$$\pi^T(z, a) = \max_{x,m,l}\{(1 - m)\varphi z(x + a)^\alpha(l + m)^\gamma \tag{3.12}$$
$$+(1 - \delta)(x + a) - lw - x[(1 + \bar{r})\mathbb{1}_{x\leq 0} + (1 + r(x, T))\mathbb{1}_{x>0}]\}$$

where $\Pi^T(z, a, \epsilon)$ is the income, after shock ϵ and the default decision, ξw is the maximum amount the entrepreneur keeps if she defaults, and $\pi^T(z, a)$ is the entrepreneurial income before the shock. $\varphi \in (0, 1]$ is the productivity in the traditional, relative to the modern sector. An entrepreneur with assets a and talent z can either invest all her assets in the production and borrow additional capital from the lenders ($x > 0$), or she can invest only part of her assets into the production and deposit the rest ($x \leq 0$). In the former case, she faces a borrowing rate $r(x, J)$, which is a function of the amount borrowed and the sector where the entrepreneur operates. In case if the agent invests less than her assets, she receives risk-free rate of interest on her deposits.

The problem of the agents entering the modern sector is similar to that of those in the traditional sector, with several slight differences:

$$\mathbb{E}(M_0(z, a, p, \epsilon)|p) = \sum_{\epsilon} M_0(z, a, p, \epsilon)\mathbb{P}(\epsilon|p) \tag{3.13}$$

$$M_0(z, a, p, \epsilon) = \max_{a',c} \{u(c) + \beta \mathbb{E}[V_{01}(z', a', p)]\} \tag{3.14}$$
$$s.t. \quad c + a' = \Pi^M(z, a, \epsilon) - \Theta\mathbb{1}_{g=0} - \tau$$
$$\Pi^M(z, a, \epsilon) = \max \left\{\pi^M(z, a) - \epsilon, \xi w\right\} \tag{3.15}$$

$$c \geq 0; \quad a' \geq 0$$

$$\pi^M(z, a) = \max_{x,m,l}\{(1 - m)z(x + a)^\alpha(l + m)^\gamma \tag{3.16}$$
$$+(1 - \delta)(x + a) - lw - x[(1 + \bar{r})\mathbb{1}_{x\leq 0} + (1 + r(x, M))\mathbb{1}_{x>0}]\}$$

where Θ is the fixed cost of entry that is paid in the beginning of the period from own assets, $\mathbb{1}_{g=0}$ equals to one if the agent enters the modern sector in the current period. Two additional differences may be noticed from the entrepreneur's problem in the traditional sector. First, the production technology in the modern sector is more productive (it depends only on entrepreneurial productivity z), and second, the beginning-of-period value functions next period allow the agent to operate in the modern sector without paying the entry fee.

From equation (3.16), one can derive the income of an entrepreneur operating a firm in the modern sector. The income depends on whether she hires external labor or not and is given by the following equations:

$$\pi^M(z,a) = \nu z^{\frac{1}{1-\nu}} \left(\frac{w}{\gamma}\right)^{\frac{\gamma}{\nu-1}} \left(\frac{\delta + \mathbb{1}_{x>0} r(x,M) + \mathbb{1}_{x\leq 0}\bar{r}}{\alpha}\right)^{\frac{\alpha}{\nu-1}} + (1 + \mathbb{1}_{x>0} r(x,M) + \mathbb{1}_{x\leq 0}\bar{r})a \tag{3.17}$$

$$\pi^M(z,a) = w\left(1 - \frac{w^{\frac{1}{\gamma}}}{\gamma} z^{-\frac{1}{\gamma}} (x+a)^{-\frac{\alpha}{\gamma}}\right) - (1 + \mathbb{1}_{x>0} r(x,M) + \mathbb{1}_{x\leq 0}\bar{r})x + (1-\delta)(x+a) \tag{3.18}$$

$$\pi^M(z,a) = \alpha(\Gamma z)^{\frac{1}{1-\alpha}} \left(\frac{\delta + \mathbb{1}_{x>0} r(x,M) + \mathbb{1}_{x\leq 0}\bar{r}}{\alpha}\right)^{\frac{\alpha}{\alpha-1}} + (1 + \mathbb{1}_{x>0} r(x,M) + \mathbb{1}_{x\leq 0}\bar{r})a \tag{3.19}$$

where $\Gamma = \frac{\gamma^\gamma}{(1+\gamma)^{1+\gamma}}$ and $\nu = \alpha + \gamma$. The income is given by equations (3.17) and (3.18) if the agent hires labor, and $m = 0$ and $m > 0$ respectively. Equation (3.19) is the income of the individual if she doesn't hire outside labor. The before-shock incomes of the entrepreneurs in the traditional sector are similar, except that the entrepreneurial talents z are multiplied with φ.

3.3.3 Entrepreneurship Choice and Default Decisions

In the model, the agents have different motivations for becoming an entrepreneur. I define an entrepreneur who prefers entrepreneurship both over wage work and unemployment to be an **opportunity entrepreneur**. This means that an opportunity entrepreneur's choice of the occupation is independent of whether she has a job offer. In contrast, I define an entrepreneur to be **subsistence**, if either she would prefer wage work over entrepreneurship but doesn't have a job offer, or she prefers entrepreneurship over unemployment, and unemployment over wage work. This means that her disutility from work for the given wage is so high, that her occupational choice does not depend on her job offer.

It can be shown from equations (3.11) & (3.15) that, all else equal, the probability that an entrepreneur defaults is decreasing with z, and conditional on z, it is decreasing in a. The reason for this is that agents with high z are more productive and generate higher profits, which makes them more willing to pay back the loan than to default. Similarly, those with higher assets will lose more if they default, in comparison to agents with lower asset endowment. On the other hand, all else equal, a higher p implies that the entrepreneur is more likely to face a production shock, thus the probability of default is weakly increasing in p. According to the definition, subsistence entrepreneurs will on average have lower entrepreneurial talents and/or higher probability of facing a shock ϵ, because their outside options of choosing the occupation are lower than the outside options of the opportunity entrepreneurs. This means that the subsistence entrepreneurs are more likely to default than the opportunity entrepreneurs, even after conditioning on assets. But then, if the lenders cannot perfectly differentiate between subsistence and opportunity entrepreneurs due to asymmetric information, for each borrowed amount of capital x in each sector they will set a borrowing rate $r(x, J)$, which will combine the default risks of all those who demand x in a given sector J, and the higher is the share of subsistence entrepreneurs in the equilibrium, the higher the equilibrium borrowing rates will be. I discuss the problem of the lenders further in sub-section 3.3.4.

Lastly, one can observe that occupational decisions are sensitive to the level of the social benefit, and that the effects are in opposite directions for the subsistence and opportunity entrepreneurs. To see this, let's first have a look at equations (3.17) and (3.19). The entrepreneurial income is a strictly increasing function of talent z. This means that $\mathbb{E}(T(z, a, p, \epsilon)|p)$ is non-decreasing in z, and there exists $\underline{z}_N(a, p)$ that makes an individual indifferent between unemployment and entrepreneurship:

$$\mathbb{E}(T(\underline{z}_N(a, p), a, p, \epsilon)|p) = N(\underline{z}_N(a, p), a, p)$$

As the value function of the unemployed is increasing in b, it follows that $\underline{z}_N(a, \kappa, p)$ is also increasing in b. In other words, everything else equal, for a higher value of the social benefit relative to the wage, the managerial talent of the threshold agent who is indifferent between staying unemployed or becoming an entrepreneur, will be higher. On the other hand, the social benefit will have a positive effect on the opportunity entrepreneurs because it will create a safety net for them in case if they face a negative shock to their entrepreneurial talent, or high production shock ϵ.

3.3.4 Capital Market

The lenders borrow capital from the world with interest rate $\bar{r}$ and lend to the entrepreneurs. They cannot fully observe the types of the borrowers. They only observe the amount an entrepreneur asks for and the sector she operates in. The fact that the entrepreneurs can default on their loans makes lending risky. The information asymmetry does not allow the lenders to provide individual specific contracts to the entrepreneurs.

Following Athreya et al. (2012), I model the capital market as a two-stage signaling game, where the entrepreneurs move first and place their asked amount x. In the second stage, the lenders set prices in a Bertrand competition, and the one with the lowest price $x(1+r(x,J))$ serves the loan. This set up excludes the possibility of 'cream skimming' due to its two-stage character and allows for pooling equilibria to arise. The borrowing interest rate is a function of the asked amount and the sector J. Due to the expected zero profit condition for the intermediaries that results from perfect competition, for each asked amount x in sector J, the borrowing rate $r(x,J)$ will solve the following equation:

$$
\begin{aligned}
(1+\bar{r})\,\overbrace{x\int_y \mathbb{1}_{g'(y)=J}\mathbb{1}_{x(y,r(x,J))=x}\,d\Psi(y)}^{\textit{Capital Demand}} &= x(1+r(x,J))\times \\
\int_y \mathbb{1}_{g'(y)=J}\mathbb{1}_{x(y,r(x,J))=x}\left[1-\sum_{\epsilon} D(y,x,r(x,J),\epsilon)\mathbb{P}(\epsilon|p)\right] d\Psi(y) && (3.20)
\end{aligned}
$$

where $y=(z,a,p,e,g)$, $g'=1$ ($g'=0$) if the agent operates in the modern (traditional) sector in the current period, $\Psi(y)$ is the equilibrium stationary distribution, $D(y,x,r(x,J),\epsilon)$ is an indicator function that equals to one if an entrepreneur with state vector y, operating in sector J, and borrowing x, chooses to default when she faces production shock ϵ. The left-hand side expression is the capital lent to entrepreneurs demanding amount x, times the cost of borrowing for the lenders. The lenders have to receive exactly the amount on the LHS in order to break even. Therefore, they will choose $r(x,J)$ such that the equality (3.20) holds, where the expression on the right-hand side is the amount they receive after default decisions, times the borrowing rate for the entrepreneurs asking for x. The expression in the square brackets on the RHS is the probability that a given type entrepreneur will pay back the loan.

It is important to note the impact of subsistence entrepreneurs on the equilibrium borrowing rate. When facing capital demand of amount x, using the stationary distribution, the lenders update their beliefs on the type distribution of the borrower and calculate her likelihood to default. The probability of default is then a non-decreasing function of the share of subsistence entrepreneurs asking for amount x. This is because, as discussed in the previous sub-section, subsistence entrepreneurs are more likely to default either because they have on average lower entrepreneurial talent, or they are more likely to face a production shock. But then a decrease in the social benefit will raise the share of subsistence entrepreneurs by decreasing their outside options and thus affect the borrowing rate and investment.

This setup has a problem of multiplicity of equilibria because the Perfect Bayesian Equilibrium (PBE) allows for different beliefs players can hold, as long as the beliefs are rational. In particular, the intermediaries can hold different beliefs over the amounts x that are never borrowed in the equilibrium. I follow Athreya et al. (2012) and use an iterative procedure to determine the equilibrium borrowing schedules that allow for highest amount of borrowing. I discuss the procedure in the numerical solution section in Appendix B.

3.3.5 Stationary Equilibrium

The stationary equilibrium of the model is characterized by the stationary distribution $\Psi(y)$ ($y = \{a, z, e, p, g\}$), which gives the joint distribution of assets, entrepreneurial talents, job offers, probabilities of facing a production shock, and an indicator of being in the modern sector in previous period in the equilibrium. The stationary equilibrium of the model is defined as the set of wage w, borrowing schedules $r(x, J)$ and lump-sum tax τ, occupational choices $o(y)$, policy functions for the workers and the unemployed $\{c(y), a'(y)\}$, and for the entrepreneurs $\{c(y, \epsilon), a'(y, \epsilon)\}$, production decisions $x(y), l(y)$, and default decisions $D(y, x, r(x, J), \epsilon)$ such that:

1. Given $\{w, r(x, J), \tau\}$, the policy functions, the production and default decisions solve the individual's utility maximization problems (3.7), (3.8), (3.10) & (3.14), and the entrepreneurs' profit maximization problems (3.12) & (3.16);

2. Given the beliefs of the lenders, the schedules $r(x, J)$, given in (3.20), are the pure-strategy Nash equilibria in the Bertrand competition game and the PBE of the signaling game;

3. Labor market clears, given by:

$$\int_y \mathbb{1}_{o(y)=W} d\Psi(y) = \int_y l^*(y) \mathbb{1}_{o(y)=S} d\Psi(y) + \int_y l^*(y) \mathbb{1}_{o(y)=B} d\Psi(y) \tag{3.21}$$

4. Government has a balanced budget:

$$\tau = b \int_y \mathbb{1}_{o(y)=N} d\Psi(y) \tag{3.22}$$

5. Given the law of motion Λ for Ψ, the latter is a fixed point: $\Lambda(\Psi) = \Psi$.

3.4 Calibration

I calibrate the model to match several stylized facts of the US economy. I use the calibrated model to study the role of social benefit b and its implications for the equilibrium occupational distribution, the share of subsistence entrepreneurs, borrowing interest rate, output per labor and investment. I then use the model to study what share of cross country differences in subsistence entrepreneurship rate, borrowing interest rate and output per labor can be explained only by the differences in social policies. In particular, I concentrate on the analysis of Chilean economy due to the data availability on the individual and macro levels, and because Chile is one of the few developing countries within the OECD member countries, and it has one of the highest entrepreneurship rates.

One period is equivalent to a year in the model. The model economy is characterized by two distributions, The entrepreneurial talent distribution and the distribution of riskiness of operating a business. I assume entrepreneurial talents are Pareto distributed, with a shape parameter η. This assumption is common in the occupational choice literature (e.g Buera and Shin, 2013; Buera et al., 2011), given the results by Axtell (2001). I assume that the riskiness types are also Pareto distributed, with shape parameter η_p, which implies that a very small share of model population faces high probabilities of a production shock. Furthermore, I model the production shock as a three-state process. The shock ϵ takes a value from the set $\{0, \bar{\epsilon}, 3\bar{\epsilon}\}$ with probabilities $\{1 - \tilde{p}, 0.7\tilde{p}, 0.3\tilde{p}\}$ respectively:

$$F_z(\tilde{z}) = 1 - \tilde{z}^{-\eta}, \quad F_p(\tilde{p}) = 1 - \left(\frac{1}{1 - \tilde{p}}\right)^{-\eta_p}$$

The distributional assumptions make the total number of parameters equal to 17. I fix eleven parameter values from the literature, while the others need to be calibrated. The fixed parameter values are given in Table 3.4.

The values of the risk-free interest rate $\bar{r}$, the discount factor β, the depreciation rate δ, the capital share in production α, the span-of-control parameter ν, and the inter-temporal elasticity of substitution parameter σ are set in the range accepted in the literature for this class of models. I take the value of the persistence of talent ϕ from Buera et al. (2011), and the relative productivity difference parameter φ from Midrigan and Xu (2014). The social benefit and the exemption level are given as shares of average income. Due to the unavailability of information on the average level of social benefits in the US, following Shimer (2005) and Poschke (2018a), I choose b equal to 40% of the equilibrium wage. The value of the exemption level is calculated in the following way: The average exemption amount across states in the US is \$ 47.800 (Mankart and Rodano, 2015), while the average wage

Table 3.4: Exogenous parameter values

Parameter	Value	Source
$\bar{r}$	0.04	Buera et al. (2011)
β	0.905	Standard
σ	2.0	Standard
ϕ	0.9	Buera et al. (2011)
b/w	0.4	Shimer (2005)
λ	0.149	Krusell et al. (2017)
δ	0.06	Standard
α	0.3	Standard
ν	0.835	Atkeson and Kehoe (2005)
φ	0.8	Midrigan and Xu (2014)
ξ	0.17	Mankart and Rodano (2015)

is \$ 48.600. According to the US Bankruptcy law, one can apply for Chapter 7 bankruptcy once every seven years, which leads to $\xi = 0.17$[18]. Lastly, I choose the probability of job loss λ such that the average job tenure is around 5.9 years, based on the findings by Krusell et al. (2017), who calculate the monthly transition probability from employment to unemployment to be 0.014.

I am left with six additional parameters, which I need to calibrate within the model. These parameters can be divided into two sub-categories: labor market related, and entrepreneurship related. The values of these parameters are presented in Table 3.5.

I choose the values of these six parameters to match six data moments in the labor market and capital market. The model generated moments and the data counterparts are presented in Table 3.6. The targeted variables are designated with asterisks.

Probability of job offer for the unemployed and disutility. Parameter μ governs the probability that the unemployed will receive a job offer next period. Therefore, everything else equal, with an increase in μ, the value function of staying unemployed will decrease, and more agents who do not have a job offer will become subsistence entrepreneurs. A higher κ, on the other hand, decreases the value function of wage work, relative to the value functions of the other occupations. Hence, I calibrate μ and κ to the equilibrium share of subsistence entrepreneurs and equilibrium employment rate.

Shape parameters and the cost of entry. In the model, the decision to become an entrepreneur primarily depends on an agent's entrepreneurial talent and her riskiness of

[18]If an individual can file for bankruptcy every seven years, this means that within a seven-year period she can get exemption of 47.800/(6*48.600)=0.17 share of her income

Table 3.5: Calibrated parameter values

Parameter	Value	Description	Parameter	Value	Description
μ	0.45	No Job Offer	Θ	13.2	Fixed Cost
κ	0.01	Disutility	η_p	10.2	Riskiness Shape
η	12	Talent Shape	$\bar{\epsilon}$	3.3	Shock Value

Table 3.6: Key statistics of the benchmark model

Distribution Moment	Value	Data	Moment	Value	Data
< 5 emp	72.07%	85.07%	Δr^*	1.08%	1.3%
< 10 emp	82.55%	91.85%	L^*	72.1%	72.9%
< 20 emp*	94.56%	95.94%	*ent. share**	8.04%	8.6%
< 50 emp	97.04%	98.5%	*sub. ent.**	21.31%	20%
< 100 emp*	98.96%	99.3%	*subtot*	1.71%	1.72%
< 250 emp	99.81%	99.75%	*Gini*	0.776	0.78

The left panel presents the fraction of firms with fewer than a given number of employees in the benchmark model and in the data. Δr^* is the borrowing interest rate spread, defined as the weighted average rate for business loans below \$ 1 mln and that for business loans above \$1 mln. L and *ent. share* are the shares of employed and entrepreneurs in the working age population that excludes people who are at school, in the army or disabled. *sub. ent.* and *subtot* are the share of subsistence entrepreneurs within all entrepreneurs and the labor force respectively. *Gini* is the Gini coefficient of wealth distribution. The asterisks indicate the calibration targets.

operating a business. Additionally, the size distribution of the entrepreneurial firms depends on the distribution of entrepreneurial talents. Therefore, I choose η and η_p to match the entrepreneurship rate and the share of firms with less than 20 employees in the data. Furthermore, for higher values of Θ, fewer entrepreneurs will choose to operate in the more productive sector, and the share of large firms will decrease. Hence, I choose Θ such that in the equilibrium the model implied share of firms with more than 100 employees is close to the data.

Parameter of production shock. Parameter $\bar{\epsilon}$ governs the default decisions of the entrepreneurs, and thus the equilibrium borrowing interest rate schedule. Less talented entrepreneurs are more sensitive to $\bar{\epsilon}$. Therefore, I calibrate $\bar{\epsilon}$ to the difference between the equilibrium average borrowing rate for amounts above \$1 million and the equilibrium average rate for amounts below \$1 million.

I compute the firm distribution moments for the US using the data from the CPS and Business Dynamics Statistics (BDS). Hipple (2010) reports that the total number of entrepreneurs in the US economy was 15.3 million in year 2009. Using the BDS data, I

Table 3.7: Model implied wealth distribution versus data

Distribution Moment	Value	PSID	SCF (2007)
$Q1$	2.51%	-0.9%	-0.2%
$Q2$	3.86%	0.8%	1.2%
$Q3$	5.01%	4.4%	4.6%
$Q4$	6.59%	13.0%	11.9%
$Q5$	82.04%	82.7%	82.5%
$90^{th} - 95^{th}$ percentile	6.47%	13.7%	11.1%
$95^{th} - 99^{th}$ percentile	14.8%	22.8%	25.3%
Top 1%	47.7%	30.9%	33.5%
$Gini$	0.776	0.77	0.78

Source: Krueger et al. (2016). The table presents the fraction of wealth owned by people in a given interval of the wealth distribution. Q1-Q5 are the first to fifth quintiles of the distribution. *Gini* is the Gini coefficient of the wealth distribution. PSID - Panel Study of Income Dynamics, SCF - Survey of Consumer Finances.

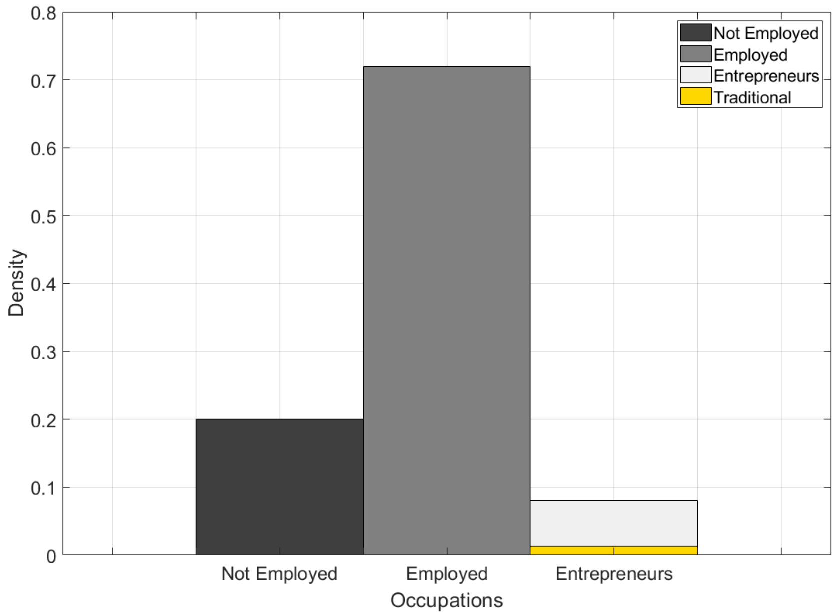
calculate the mean number of employer firms for the years 2010-14 to be around 5 million. Combining these two results, one can calculate the shares of non-employer and employer firms in the US economy, which is around 66.6 and 33.4 percent respectively. Next, I use the firm size tabulations in the BDS to construct the firm distribution statistics, again as averages for the years 2010-14. I take the share of subsistence entrepreneurs in total entrepreneurship from Fairlie et al. (2015). The entrepreneurship rate and employment rate as shares of labor force[19] are calculated from CPS for the years 2010-2015. The borrowing interest rate spread ($\Delta\hat{r}$) is defined as the average borrowing rate for loans lower than one million dollars, minus the average rate for loans above one million. I use the 2016 FED Survey of Business Lending for the calculation.

The model generated moments match the data quite well, taking into consideration the complexity of the model. The main difficulty arises when matching the entrepreneurship rate and the borrowing interest rate spread to their data counterparts. This is due to the fact that in order to increase the borrowing rate spread one needs to generate a high likelihood of default, which means that the shock $\bar{\epsilon}$ needs to go up, but this makes individuals reluctant to switch to entrepreneurship.

The model implied firm distribution resembles the data relatively well, even though only two moments of the distribution are targeted. Additionally, the external finance-to-output ratio in the model is 2.16, close to the ratio of 2.5 for the US (Buera et al., 2011), and the

[19] I refer to the labor force as the total number of 18-65 year old population, who are not disabled, retired or involved in education. This includes not only the employed (employees and entrepreneurs) and the registered unemployed, but also the not-employed.

Figure 3.5: Model implied occupational distribution in the baseline model



model implied wealth distribution is comparable with the data, as can be seen from Table 3.7[20].

3.5 Results

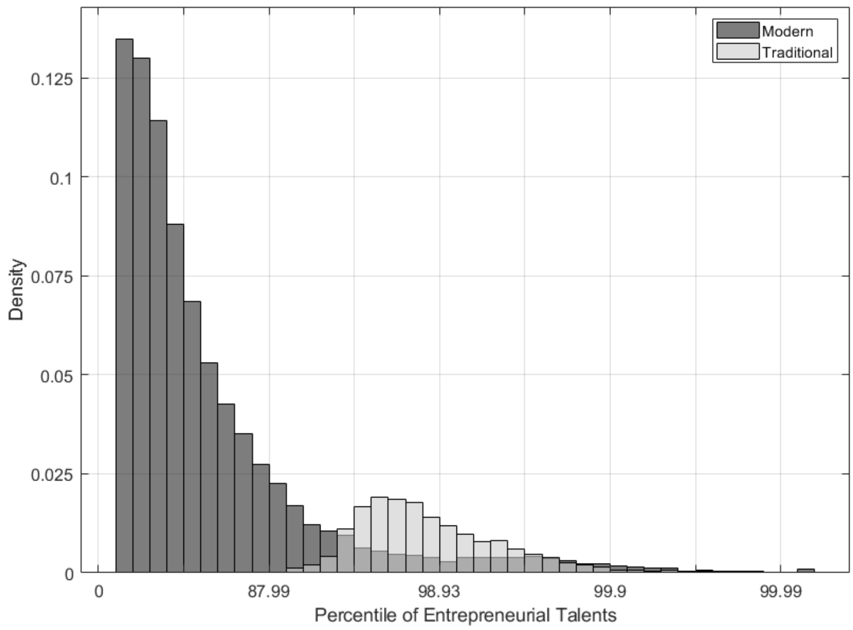
The Occupational Distribution

Figure 3.5 plots the equilibrium occupational distribution implied by the benchmark model. In every period, around 72.1 percent of the population is employed, and 8.04 percent are entrepreneurs similar to the data. The agents choose the entrepreneurial occupation either out of necessity (subsistence entrepreneurs), or because they want to pursue an opportunity (opportunity entrepreneurs). Using the definitions of subsistence and opportunity entrepreneurs developed in sub-section 3.3.3, I calculate the share of subsistence entrepreneurs in the population of entrepreneurs to be 21.4% in the benchmark calibration, close to 20 percent in the data.

As we can see from Figure 3.5, the majority of the entrepreneurs operate in the modern sector. The traditional sector serves as a platform for entrepreneurs to accumulate enough assets and pay the cost of entry to the more productive sector. This is because due to the timing of the model the agents do not have access to external finance at the beginning of the period, when they have to pay the entry cost, and therefore they have to pay it from

[20]The model implied wealth distribution is plotted in the Appendix Figure B.6.

Figure 3.6: Entrepreneurial talent distribution by sector in the baseline model



This figure visualizes the histograms of the entrepreneurial talents in the traditional and modern sectors. The sum of the masses of the histograms is normalized to one. x-axis is the percentile of the entrepreneurial talent distribution of the population.

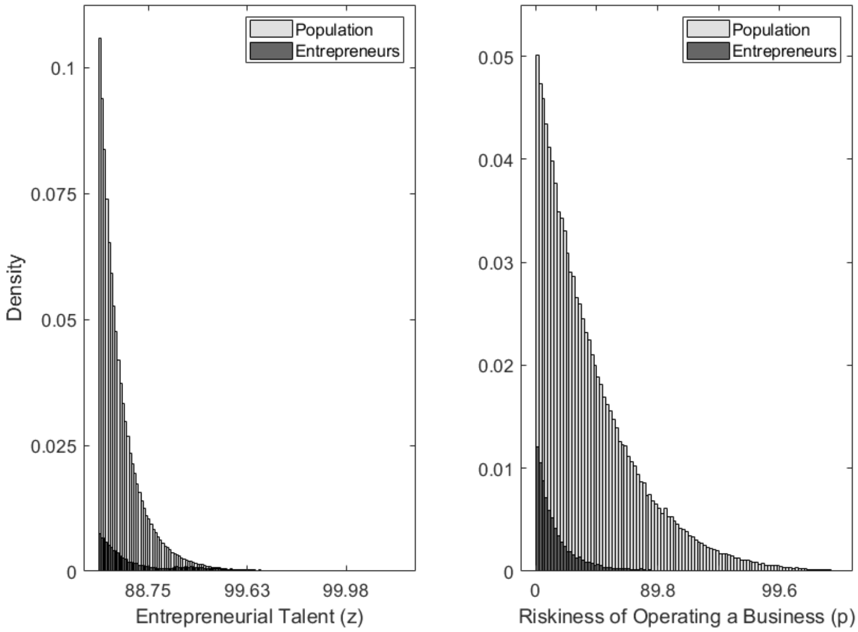
their own assets. This behaviour can be observed from the model implied entrepreneurial talent distributions in each sector, shown in Figure 3.6.

In the benchmark calibration, the traditional sector mainly attracts agents with high entrepreneurial talents, who can accumulate assets as entrepreneurs and move to the modern sector. Low talented agents, on the other hand, prefer to stay unemployed or to work as an employee. In contrast, the entrepreneurial talent distribution in the modern sector has a fat left tail. This is due to the fact that many entrepreneurs in the modern sector do not move to unemployment immediately after their talents are redrawn. If they continue operating in the modern sector, there is a positive probability that the next period they may receive a high entrepreneurial talent and increase their profits, whereas, if they move to unemployment, next period they will lose the access to the modern sector unless they pay the fixed cost of entry again. This means that the low talented entrepreneurs operate not only in the traditional, but also in the modern sector, affecting the borrowing interest rates in both sectors.

The Entrepreneurs

In order to better understand the channels through which social policy affects the occupational distribution, it is important to study who becomes an entrepreneur in the benchmark

Figure 3.7: Riskiness of operating a business and entrepreneurial talent distributions for the entrepreneurs and the population: Benchmark model

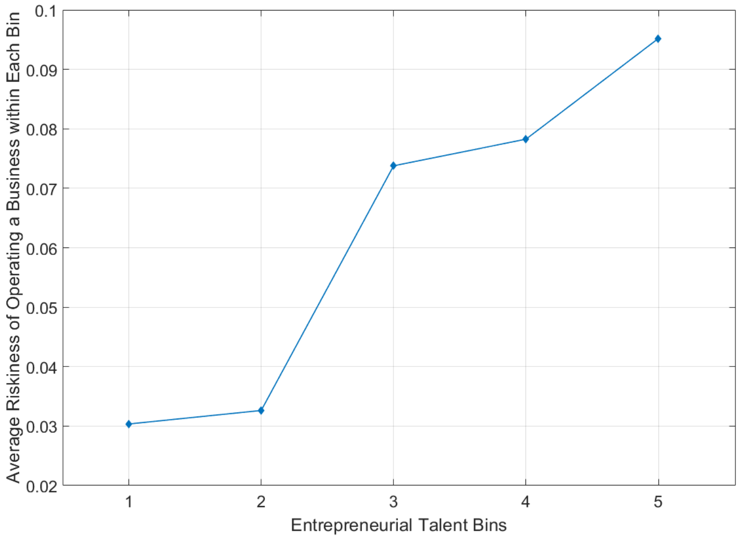


This figure visualizes the model implied equilibrium distributions of entrepreneurial talent z (left panel) and riskiness of operating a business p (right panel) for the entrepreneurs and the entire population in the benchmark calibration. The x-axes are the percentiles of the respective distributions. The entrepreneurs have higher talents and are less likely to face a production shock.

model. Figure 3.7 plots the equilibrium distributions of the riskiness of operating a business (p) and entrepreneurial talents (z) for the entrepreneurs and the total population in the benchmark model. As expected, the agents with higher talents are more likely to become entrepreneurs, and there exists a threshold talent $\bar{z}$, above which everybody chooses the entrepreneurial occupation (this result is better illustrated in Figure B.5 in the Appendix). The relationship is reversed for the riskiness of operating a business. As we can see from the figure, agents with higher riskiness p are less likely to become entrepreneurs, and the likelihood reaches zero for very high values of p. The agents with low entrepreneurial talents and relatively high riskiness of operating a business prefer the wage work if they have a job offer, otherwise they stay unemployed. The reason for the latter is twofold. First, as unemployed they receive social benefit b, which may be higher than their expected income as entrepreneurs. Second, in contrast to staying unemployed, agents do not receive a job offer in the next period if they become entrepreneurs. As the social benefit is high enough, the agents do not have to earn income for subsistence and prefer to stay unemployed longer until a job offer arrives.

Furthermore, the threshold value of the riskiness of operating a business that makes an agent indifferent between becoming an entrepreneur and staying in the labor market is

Figure 3.8: The relationship between riskiness of operating a business and entrepreneurial talents for the entrepreneurs



The equilibrium distribution of entrepreneurial talents is divided into five bins, and for each bin, the average riskiness of operating a business p of entrepreneurs with talents within that bin is plotted in the figure. The horizontal axis gives the indices of the bins. The bins with higher indices include talents from the higher percentiles of the distribution.

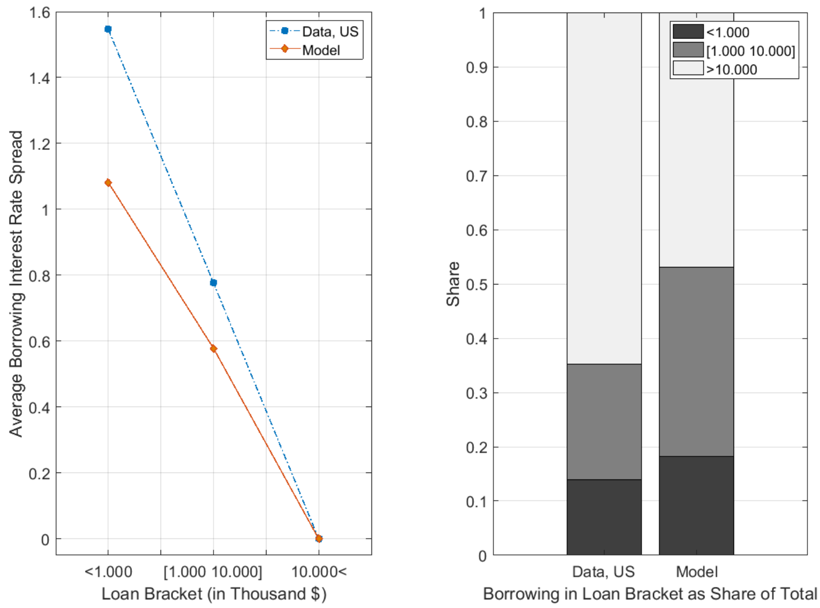
increasing with the entrepreneurial talent. Figure 3.8 plots the average riskiness of operating a business of entrepreneurs with talents in a given interval of entrepreneurial talent distribution. The positive relationship is quite intuitive: as already discussed, when high talented agents face a production shock, it takes away a relatively small share of their total income, a large part of the income is available for consumption and saving, therefore, they will choose the entrepreneurial occupation even if their riskiness is high. In contrast, a given production shock is much more costly for the low talented entrepreneurs. Therefore, the higher is a low skilled agent's p, the lower will be the expected returns from entrepreneurial occupation, possibly lower than the value of staying unemployed.

This relationship implies that larger firms are more likely to face a production shock on average, but it does not mean that larger firms are also more likely to default in the model. This is because the entrepreneurs operating the large firms have higher income and more assets, therefore, in case if they are hit by a production shock, they are better off by absorbing it than defaulting.

The Capital Market

In the model, the lenders only observe the amounts the entrepreneurs borrow and the sector they operate in. The individual characteristics of the borrowers are unobservable. There-

Figure 3.9: Comparison of the average borrowing interest rates for different loan sizes for the US versus the baseline model



The left panel illustrates the relationship between loan size and the average borrowing rate spread in the model and in the data. The average borrowing rate spread is the difference between the average rate for a given size minus the average rate for loans larger than $10 mln. In the model, similar to the data, the average rate is calculated as the weighted sum of the effective borrowing interest rates for loans within the given bracket. The data on the borrowing rates in the US is taken from the Surveys of Terms of Business Lending (Jan 2016-May 2017). The right panel presents the sum of loans in each size bracket as a share of total loans. The values in the legend of the right panel, and in the horizontal axis of the left panel are in thousand dollars.

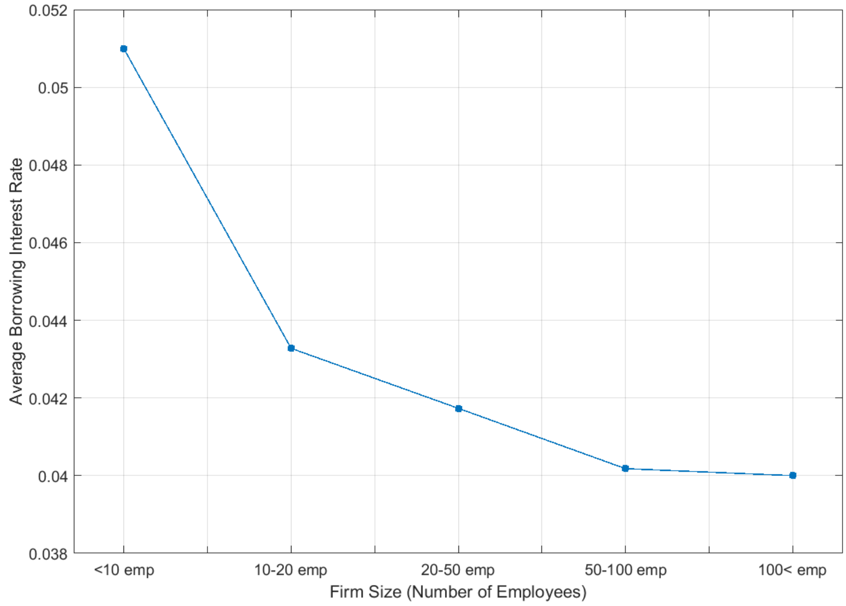
fore, the equilibrium borrowing interest rates in each sector are functions of the borrowed amounts.

The left panel of Figure 3.9 compares the model implied borrowing rate schedule[21] as a function of borrowed amount with the data. We can see that, consistent with the data, the model implied borrowing interest rate is decreasing in the borrowed amount. In the model, this is because the capital the entrepreneurs invest is positively correlated with their entrepreneurial talents. The entrepreneurs with higher talents operate more productive technologies, they generate higher profits and, therefore, they borrow higher amounts and are less likely to default when facing a production shock.

The right panel of Figure 3.9 provides further validity to the model performance. It compares the total values of loans in three size intervals (as shares of the total borrowed capital) in the US versus the model. The share of firm loans below $1 mln is 13.85 percent for the US, while it is 18.2 percent in the model. The share of loans between $1 and $10 mln is slightly lower in the data, 21.4% versus 34.8% in the model. It needs to be mentioned

[21]The figure presents the average interest rates for the amounts actually borrowed.

Figure 3.10: Model implied borrowing interest rate schedule, as a function of firm size



The average borrowing interest rate for each bracket is defined as the weighted average of the interest rates with which firms within a give size bracket borrow capital.

that the model does quite well in replicating the key facts of the market for firm loans in the US, even though only one data moment, the average borrowing rate spread, is targeted.

Next, I study the model implied access to finance for small versus large firms. Figure 3.10 presents the relationship between firm size and the borrowing interest rate. The borrowing rate spread for the small firms (less than ten employees) relative to large firms is 1.1 percentage points. The spread decreases to 0.33 percentage points for firms of size 10-20 employees and it is 0.17 percentage points for firms with 20 to 50 employees. In my model, the production shock enters as an additive term in the profit function. Therefore, in relative terms, a given realization of the production shock will be stronger for the entrepreneurs with low entrepreneurial talents, and hence, the smaller firms are more likely to default. The model implied negative relationship between firm size and the borrowing interest rate is consistent with the findings in the empirical literature that SMEs are more financially constrained than larger firms (e.g. Bougheas et al., 2006; Beck et al., 2006; Coluzzi et al., 2015). Here it needs to be mentioned that, in comparison to the model I propose, the standard models with collateral constraints do not perform well at capturing the positive relationship between firm size and leverage observed in the data[22].

To summarize, the model captures the key features of the US capital market fairly well.

[22]Using Orbis and Amadeus databases for European firms, Gopinath et al. (2017) find that large firms are more leveraged than small firms. They develop a model with size dependent borrowing constraint, and show that it better matches the data than the models with financial constraints independent of firm size.

It also provides reasonable predictions of the selection into entrepreneurship and the role of the social benefit in occupational choice. Additionally, the model does well at capturing several non-targeted moments, such as the firm distribution, the wealth distribution and the external finance-to-output ratio in the US economy. Therefore, in the following I use the model to study the role of the social benefit in explaining the differences in occupational distributions, firm distributions, access to finance and output-to-labor ratio across countries.

3.5.1 Cross-Country Quantitative Analysis

In this subsection, I study the implications of the benchmark model for an economy with low social benefit. I choose the economy of Chile for the cross-country analysis. My choice is motivated by the fact that Chile has one of the highest entrepreneurship rates and it is comparatively less developed within the OECD countries. The data availability on the individual and economy levels serves as another important factor for the choice.

In the counter-factual analysis, I feed the model with the average social benefit an unemployed person receives in Chile and solve for the equilibrium. I then study the model implied occupational distribution, access to finance, output-to-labor ratio and other macroeconomic variables and compare them to the data, to see what share of the cross-country differences in these variables can be explained by the difference in the levels of social benefit and the entrepreneurship rates.

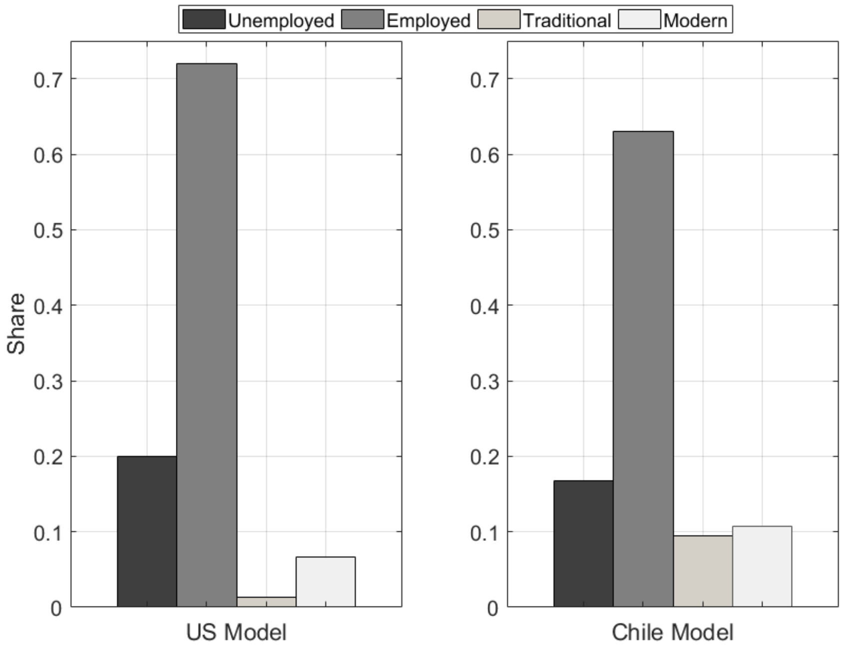
Chilean Data

The model implications are for the working age population who are capable of work and are not involved in other activities (e.g. education, military). Therefore, for the analysis I first need to construct a data set of the Chilean population that is comparable with the model. I use the 2015 National Socio-economic Characterization Survey of Chile (Casen) for this purpose.

Casen is conducted once every two to three years, and the unit of observation is the household. In each survey, around one percent of the households are sampled in a way that the survey is representative for the entire population of the country. The survey is mainly used for the analysis of poverty and labor statistics in the country, and therefore it serves well to the purpose of the analysis in this section. I keep only the male population of age between 18 and 64 in the data set, dropping the students, the disabled and retired people out of the sample[23].

[23]Labor force participation rates of females are significantly lower than the participation rates of males

Figure 3.11: Comparison of model implied occupational distributions for the US and Chile



The data analysis shows that around 20.5 percent of the sample population in Chile are entrepreneurs, in comparison to only 8.6 percent of the sample in the US. Additionally, 67.7 percent in Chile are employees[24], much lower than the share of employed of 72.9 percent in the US.

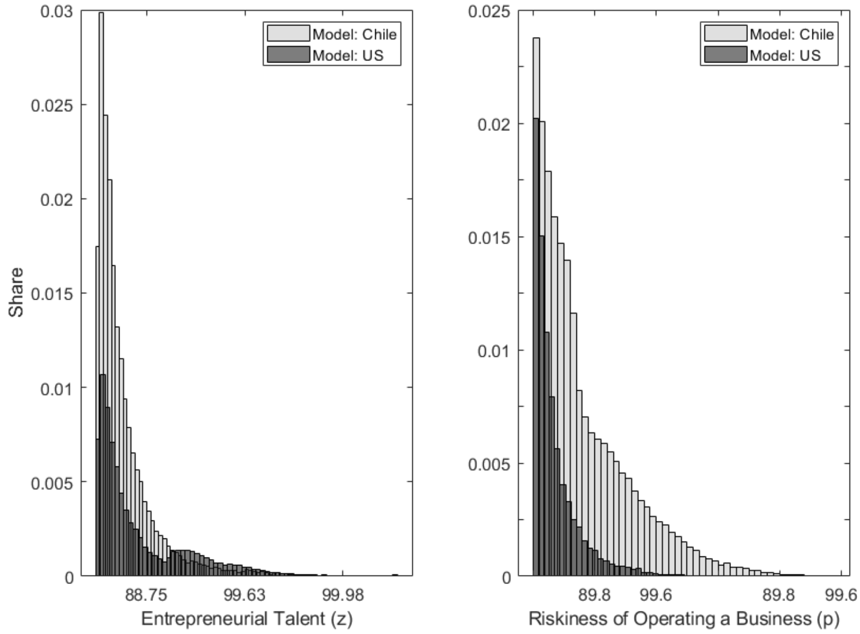
I then calculate the sum of government provided social and unemployment benefits an average unemployed person receives in Chile. Specifically, the survey participants are asked which government provided subsidies and payments their household received during the month prior to the survey and in what amount. Among others, the list of benefits includes the unemployment insurance payments, family protection, retirement and disability subsidies, assistance related to child birth or disability of a family member, and drinking water subsidies. I calculate the weighted average amount an unemployed person received during the month prior to the survey and divide it by the average before-tax monthly wage for year 2015[25]. The data shows that an average unemployed person received only around 2.53 percent of the average before-tax monthly salary during the month prior to the survey, and an average employed person received around 1.6 percent. Therefore, in the counter-factual

in developing countries, and Chile is not an exception. The reasons for the existence of the gap are mainly cultural and are orthogonal to the analysis in this chapter.

[24]I define a person to be employed if, according to his answers to the survey questions: (i) he worked for money or in kind for at least one hour in the previous week, or (ii) he has a job but was temporarily absent during the previous week. A person is defined to be an entrepreneur if, according to his answers to the survey questionnaire, he is an employer or an own account worker in his job.

[25]Source: OECD Database, 2015.

Figure 3.12: Comparison of model implied entrepreneurial characteristics in Chile and in the benchmark model



This figure plots the model implied equilibrium distributions of entrepreneurial talent z (left panel) and riskiness of operating a business p (right panel) for the entrepreneurs in the benchmark calibration and in the model for Chile. The x-axes are the percentiles of the respective distributions. The y-axes are the shares in total population. In the model for Chile, the entrepreneurs have lower entrepreneurial talents and are more likely to face a production shock on average.

analysis, I choose the value of the social benefit in the model such that the social benefit is 2.5 percent of the equilibrium before-tax wage.

Occupational Distributions

Figure 3.11 plots the model implied occupational distributions for the US and Chile. As expected, the decline in the social benefit leads to a significant increase in the entrepreneurship rate. It goes up by around 12 percentage points in the model that replicates the economy of Chile, reaching near the data value of 20.2%. This increase in the entrepreneurship rate is compensated by 9.1 percentage point decline in the employment rate in the model, and around 3.1 percentage point reduction in the non-employment rate. The model predicted employment rate for Chile goes down to 63%, lower than 67.7% in the data. The decline in the employment rate, similar to Poschke (2018b), is due to the fact that the entrepreneurs do not receive a job offer in the model. Hence, the higher is the equilibrium share of entrepreneurs in the model, the lower the share of population receiving a job offer will be.

We can see from Figure 3.11 that the main increase in the entrepreneurship rate happens in the traditional sector. In comparison to the benchmark model (left panel of Figure 3.11), the entrepreneurship rate in the traditional sector increases by 8.1 percentage points in Chile, and that in the modern sector goes up by four percentage points. This can be either because the new entrepreneurs do not have enough assets to pay the cost of entry, or because they do not find it optimal to enter the modern sector due to their low entrepreneurial talents and/or high risk.

To further analyze this question, we need to study the skill distribution and the motivations of the new entrant entrepreneurs. Further analysis of the entrepreneurial composition reveals that around 68.8 percent of these entrepreneurs are subsistence in Chile, according to the definition in sub-section 3.3.3. This is more than 3 times higher than the share of subsistence entrepreneurs in the benchmark model, and higher than the average subsistence entrepreneurship rate of 30 percent in the data, according to the surveys by GEM[26]. Figure 3.12 compares the skill distributions of entrepreneurs in the calibration with low social benefit and that in the benchmark model. It can be seen that on the entrepreneurial talent dimension (left panel), the new entrants have lower skills, and on the dimension of riskiness of operating a business (right panel), they are on average more risky, which implies that the entrepreneurs entering after the decline in the level of social benefit are on average more likely to default on their loans.

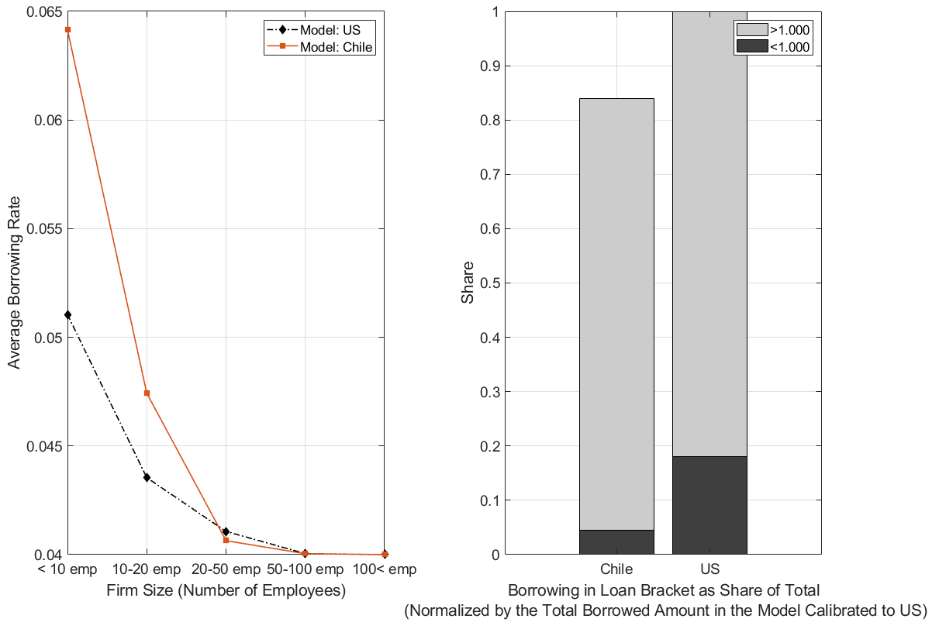
Access to Finance

The worsened composition of entrepreneurs and the information asymmetry force the lenders to charge higher borrowing rates from SMEs relative to large businesses. The borrowing interest rate spread, defined as the difference between the average effective rate for loans smaller than $1 mln and average rate for loans above $1 mln, goes up from 1.08 percentage points in the benchmark calibration to 3.47 percentage points in the model replicating the economy of Chile. According to the OECD database, the average interest rate spread between SMEs and large firms for years 2013 to 2015 was 6.31 percentage points in Chile, which means that only the increase in the entrepreneurship rate due to the lower social insurance can explain around 55 percent of the borrowing interest rate spread in the data. This result illustrates that a significant share of cross-country differences in SME borrowing rate spreads can be explained by entrepreneurship rate differences driven by differences in social benefits.

Figure 3.13 compares the model implied loan size and prices for Chile with those in the

[26]The average subsistence entrepreneurship rate within the universe of new businesses (up to three years of age) in the US is 16% in the GEM database while for all businesses, it is around 10 percent. Fairlie et al. (2015) reports the share of subsistence entrepreneurs to be 20 percent in the US (the value I use for calibration), much closer to the 16 percent for new businesses. Therefore, for the comparison of the model with the data, I use the share of subsistence entrepreneurs in new businesses reported by GEM.

Figure 3.13: Model implied access to finance by firm and loan size for Chile and the US.



The left panel of the figure plots the average effective borrowing interest rates firms of given size (in number of employees) face in the equilibrium. The right panel plots the shares of capital borrowed in loans of size below \$1 mln and above \$ 1 mln. The total capital borrowed in the benchmark model is normalized to one. The total capital borrowed in the model for Chile is relative to that in the benchmark model.

US. Similar to the benchmark model, the borrowing rate is decreasing in firm size, as it can be seen from the left panel of the figure.

The model predicts that small firms of size up to 20 employees pay a higher premium for loans in the model of Chile, relative to the firms in the benchmark model. The average rates at which firms borrow in the model of Chile have risk premia of 2.05 and 0.74 percentage points for firms with up to ten employees and with ten to twenty employees respectively, in comparison to risk premia of 1.1 and 0.33 percentage points in the benchmark model. This naturally affects the demand for capital. The total capital borrowed by all entrepreneurs in Chile, as predicted by the model, declines to only 84.3 percent of the borrowed capital in the benchmark model. The right panel of Figure 3.13 visualizes the capital borrowed in Chile, relative to the benchmark model. We can see that the share of loans below \$1 mln decreases from 18.2 percent in the benchmark model to around six percent, even though the number of small firms increases. This result implies a significant negative effect of firm composition on small firms' access to finance both on the intensive and extensive margins.

Aggregate Effects

The decrease in the social benefit naturally has its consequences on the aggregate economy through its effects on the occupational distribution and the capital market. Table 3.8

Table 3.8: Aggregate statistics under policy regimes in Chile and US

variable	Model:Chile	Model:US
Firm Distribution		
< 5 emp	89.38%	72.07%
< 10 emp	95.49%	82.55%
< 25 emp	97.36%	94.56%
< 50 emp	99.11%	97.04%
< 100 emp	99.77%	98.96%
< 250 emp	99.96%	99.81%
Aggregate Variables		
employed	63.03%	72.1%
Y/L	91.61%	100%
B/Y	1.914	2.16
entrep	20.02%	8.04%
$\Delta\tilde{r}$	3.47%	1.08%
sub-entrep	68.78%	21.31%
trad	9.46%	1.34%

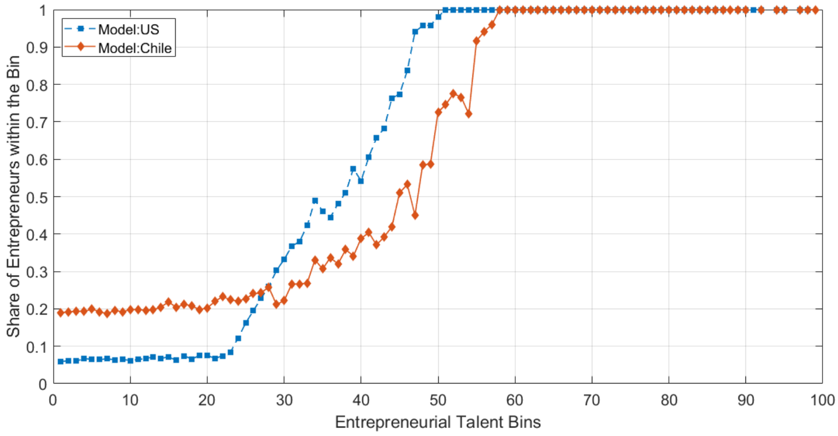
The firm distribution is presented as the fraction of firms below a given size. *employed*, *entrep* - the share of agents who are employees and entrepreneurs respectively in the model, Y/L - equilibrium output-to-labor ratio (total output divided by the sum of employees and entrepreneurs), B/Y - external finance-to-output ratio (total borrowed amount divided by total output), $\Delta\tilde{r}$ - borrowing interest rate spread, $sub - entrep$ - the share of subsistence entrepreneurs within all entrepreneurs, *trad* - the share of entrepreneurs operating in the traditional sector.

summarizes the model implied aggregate effects of the decline in the social benefit. As already discussed, the increase in the entrepreneurship rate leads to a compositional change within entrepreneurs and affects the average borrowing interest rate. The higher risk premia that entrepreneurs face affect their investment decisions. This can be seen from the decline in the external finance-to-output ratio (B/Y) by around 11.6 percent in the economy with lower social benefit. The worsened credit conditions, combined with the fact that the new entrant entrepreneurs have on average lower entrepreneurial talents, lead to resource misallocation in the capital and the labor markets[27], and negatively affect the economy level labor productivity, measured by the output-to-labor ratio (Y/L). From Table 3.8, we can see that the output-to-labor ratio goes down by 8.4 percent in Chile, which is around 15.8 percent of the difference in output-to-labor ratio between the US and Chile[28].

[27]Given that agents in the model do not receive a job offer while in the entrepreneurial occupation, a higher share of entrepreneurs leads to misallocation of labor, as the newly entering entrepreneurs have lower entrepreneurial talents and they would have been more productive if they were employed.

[28]See Appendix B.2 for the details.

Figure 3.14: The relationship between entrepreneurial talent and the likelihood of becoming an entrepreneur in the benchmark model and the model replicating Chile



To plot the figure, I first partition the equilibrium entrepreneurial talent distribution into equidistant bins. For each bin, I then calculate the share of entrepreneurs in the population with talents within the bin. The horizontal axis presents the order of the bins. A higher order means that the bin includes entrepreneurial talents on the higher percentiles of the distribution.

The worsened credit conditions also distort the occupational choices of the agents. In particular, a significant share of agents who were better off as entrepreneurs in the model with the benchmark calibration choose other occupations in the model with low social benefit, due to a higher wage level and borrowing interest rates. Figure 3.14 visualizes this result. We can observe that the low talented agents are almost twice as likely to become entrepreneurs in the economy replicating Chile. This pattern changes for the medium skilled agents, who are now less likely to become entrepreneurs relative to the benchmark model, and the threshold entrepreneurial talent, above which everyone becomes an entrepreneur, shifts to the right. This result translates into differences in the firm size distributions, as presented in Table 3.8. The share of firms with less than ten employees increases dramatically in the economy with lower social benefit, from 82.6 percent in the benchmark economy to 95.5 percent in Chile, which is close to the same statistic of 96.7 percent in the data for Chile (see Table 3.9). This result is consistent with the findings in the literature that firm size distributions in developing countries are characterized by a large share of small firms (e.g. Gollin, 2008; Hsieh and Olken, 2014; Poschke, 2018a).

To summarize, the model predicts that the difference in occupational distributions between the US and Chile due to the differences in social insurance can explain around 16% of the difference in the output-to-labor ratios between the countries. The lower social benefit explains almost all of the difference in entrepreneurship rates between the US and Chile, and predicts a lower employment rate for Chile than in the data. Furthermore, the consequent worsening of the composition of entrepreneurs due to lower social benefit leads to an increase in equilibrium borrowing interest rates and explains around 48% of the difference

Table 3.9: Comparison of model predicted moments with data for Chile

variable	Model:Chile	Data:Chile
< 5 emp	89.38%	94.28%
< 10 emp	95.49%	96.70%
< 50 emp	99.11%	99.03%
Employed	63.03%	66.90%
Entrep	20.02%	20.50%
$\Delta\tilde{r}$	3.47%	6.31%
Sub-entrep	68.78%	30%
Y/L	91.61%	46.79%

Source: Casen 2015. The output-to-labor ratio Y/L is relative to US.

in borrowing interest rate spreads between the countries, which depresses the investment and leads to capital misallocation. Finally, the model implied firm distribution for Chile is characterize with a higher share of small firms, consistent with the data.

3.6 Conclusion

In this chapter, I show that across countries: (i) higher entrepreneurship rate is associated with a higher share of subsistence entrepreneurs, and a higher borrowing interest rate spread for SMEs, (ii) the entrepreneurship rate declines with the increase in the replacement rate of unemployment insurance. I propose a quantitative theory that explains these facts and use it to quantify the importance of social insurance in explaining the cross country variation in occupational distribution, entrepreneurial composition, access to finance and labor productivity.

I develop a model of occupational choice, where agents choose between wage work, if they have a job offer, entrepreneurship and non-employment. In the latter case they receive a social benefit. The agents become entrepreneurs either to pursue an opportunity, or out of necessity, the outside option of the latter being the social benefit. The entrepreneurs can borrow capital in the financial market. The information asymmetry and limited commitment of the entrepreneurs force the lenders to consider the composition of the entrepreneurs when pricing the loans. Lowering the social benefit raises the share of necessity driven entrepreneurs, decreases the employment rate and forces the lenders to raise the borrowing interest rates.

I calibrate the model to match several salient features of the US economy and use the social benefit as the only policy tool to evaluate the model predictions for the economy of Chile. I feed the average social benefit the unemployed receive in Chile into the model and study the model implications. The model does well in explaining the differences in occupational and firm distributions across the countries. It predicts that the rise in the entrepreneurship rate is mainly due to the increase in the share of subsistence entrepreneurs. Furthermore, the channel of social insurance alone explains around 55% of the borrowing rate spread for SMEs in Chile due to the increase in the entrepreneurship rate, which leads to resource misallocation in the labor and capital markets and affects the output-to-labor ratio. The model predicts that the difference in occupational distributions due to differences in social benefits can explain 15.8% of the difference in output-to-labor ratio between Chile and the US.

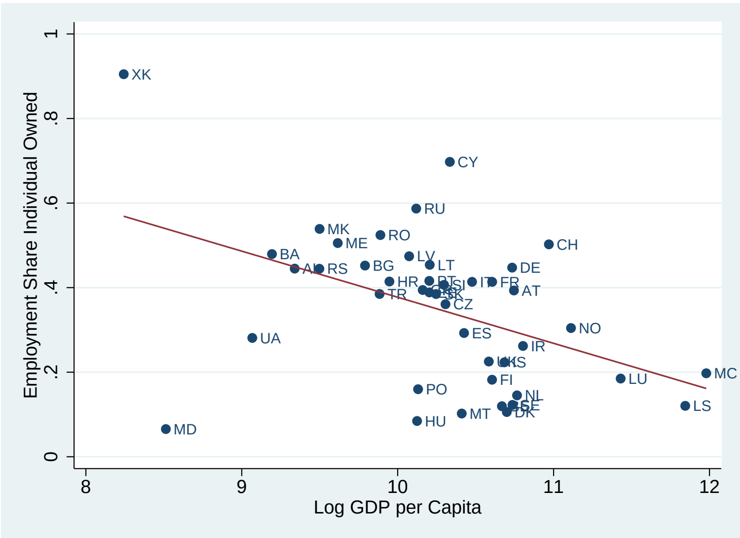
These results show that the social insurance is an important policy tool in developing countries as it not only creates a safety cushion for the poor and unlucky, but it also can affect the resource allocations in the labor and capital markets through its effects on the occupational decisions. In particular, higher social benefits in developing countries will allow the unemployed to spend more time on job search instead of transitioning to entrepreneurship out of necessity, thereby helping them to choose the occupation that best suits their abilities. Hence, only those pursuing an opportunity will become entrepreneurs and they will face better access to finance. This will increase the economy level investment and mitigate the capital misallocation on the economy level.

Appendix A

Appendix to chapter 1

A.1 Additional Figures

Figure A.1: Scatterplot of the share of workforce employed by individual owned firms and log GDP per capita of European countries



Data: Amadeus database and CIA Factbook, year: 2014

A.2 Calculation of TFP

Let the equilibrium measure of hired managers in the market be $\mu_M = \int_{\underline{z}^M}^{z_{max}} dF_z(\tilde{z}|p=0)$. The manager of talent $z^M[i]$ will be assigned to the owner of project $p[i]$ in the equilibrium, and together they will produce output, given by:

$$y^*[i] = \phi(z^M[i], p[i])^\nu (k^*[i]^\alpha l^*[i]^{(1-\alpha)})^{1-\nu} \tag{A.1}$$

where $k^*[i]$ and $l^*[i]$ are the profit maximizing inputs of capital and labor and are given by:

$$k^*[i] = \phi(z^M[i], p[i]) \left(\frac{r+\delta}{\alpha}\right)^{\frac{(1-\nu)(1-\alpha)-1}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)}{\nu}} (1-\nu)^{\frac{1}{\nu}} \tag{A.2}$$

$$l^*[i] = \phi(z^M[i], p[i]) \left(\frac{r+\delta}{\alpha}\right)^{\frac{(\nu-1)\alpha}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)+\nu}{\nu}} (1-\nu)^{\frac{1}{\nu}} \tag{A.3}$$

Then, the total capital borrowed and labor hired by firms with outside managers will be:

$$K_M = \mu_M \int_0^1 k^*[i]di = \left(\frac{r+\delta}{\alpha}\right)^{\frac{(1-\nu)(1-\alpha)-1}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)}{\nu}} (1-\nu)^{\frac{1}{\nu}} \mu_M \int_0^1 \phi(z^M[i], p[i])di \tag{A.4}$$

$$L_M = \mu_M \int_0^1 l^*[i]di = \left(\frac{r+\delta}{\alpha}\right)^{\frac{(\nu-1)\alpha}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)+\nu}{\nu}} (1-\nu)^{\frac{1}{\nu}} \mu_M \int_0^1 \phi(z^M[i], p[i])di \tag{A.5}$$

Similarly, total capital and labor hired by project owners who don't enter the market for managers will be as follows:

$$K_O = \left(\frac{r+\delta}{\alpha}\right)^{\frac{(1-\nu)(1-\alpha)-1}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)}{\nu}} (1-\nu)^{\frac{1}{\nu}} \int_p \int_{\underline{z}(p)}^{z_{max}} \phi(z^O, p) dF_z(\tilde{z}|p) dF_p(\tilde{p}) \tag{A.6}$$

$$L_O = \left(\frac{r+\delta}{\alpha}\right)^{\frac{(\nu-1)\alpha}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)+\nu}{\nu}} (1-\nu)^{\frac{1}{\nu}} \int_p \int_{\underline{z}(p)}^{z_{max}} \phi(z^O, p) dF_z(\tilde{z}|p) dF_p(\tilde{p}) \tag{A.7}$$

Let the sum of the integrals over all firm technologies be given by Z:

$$Z = \int_p \int_{\underline{z}(p)}^{z_{max}} \phi(z^O, p) dF_z(\tilde{z}|p) dF_p(\tilde{p}) + \mu_M \int_0^1 \phi(z^M[i], p[i])di$$

Then the total capital and labor hired in the equilibrium will be:

$$K = K_M + K_O = Z \left(\frac{r+\delta}{\alpha}\right)^{\frac{(1-\nu)(1-\alpha)-1}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)}{\nu}} (1-\nu)^{\frac{1}{\nu}} \tag{A.8}$$

$$L = L_M + L_O = Z \left(\frac{r+\delta}{\alpha}\right)^{\frac{(\nu-1)\alpha}{\nu}} \left(\frac{1-\alpha}{w}\right)^{\frac{(1-\nu)(1-\alpha)+\nu}{\nu}} (1-\nu)^{\frac{1}{\nu}} \tag{A.9}$$

From equations (A.2),(A.3) and (A.8),(A.9) one can derive individual choices of capital and labor as functions of the aggregates:

$$k^*[i] = \frac{\phi(z^M[i], p[i])}{Z} K$$
$$l^*[i] = \frac{\phi(z^M[i], p[i])}{Z} L$$

and the individual and total output will be respectively:

$$y^*[i] = \frac{\phi(z^M[i], p[i])}{Z^{1-\nu}} \left(K^\alpha L^{1-\alpha}\right)^{1-\nu} \tag{A.10}$$
$$Y^* = \int_p \int_{\underline{z}(p)}^{z_{max}} y^*(z^O, p) dF_z(\tilde{z}|p) dF_p(\tilde{p}) + \mu_M \int_0^1 y^*[i] di = Z^\nu (K^\alpha L^{1-\alpha})^{1-\nu} \tag{A.11}$$

where Z^ν is the total factor productivity.

Appendix B

Appendix to chapter 2

B.1 Appendix

Table B.1: Occupational distribution, model versus data: Mexico

variable	Model:Mexico	Data:Mexico
Employed	60.80%	65.20%
Entrep	23.13%	23.10%
Sub-entrep	74.45%	19.0%

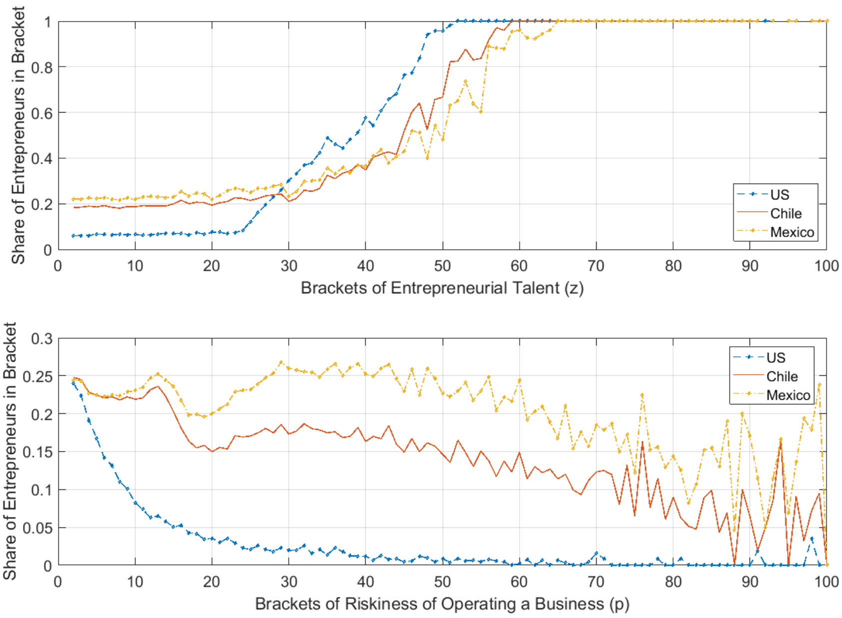
The employment and entrepreneurship rates are calculated as shares of working age (male) population who are capable of work, are not students, or retired. The data sources are: IPUMS-International, 2010 and GEM.

In this Appendix section, I conduct a robustness check of the main results, where I analyse the model implications for Mexico. I use the 2010 General Housing and Population Census of Mexico to study the occupational distribution in the economy. The Census is conducted every five years and the unit of observation is the household, with a representative sample size of around ten percent of the population. I use the version of the Census constructed and harmonized by IPUMS-International[1] (Minnesota Population Center). Similar to the main analysis, I concentrate only on the male population of age between 18 and 65, who are capable of work, are not retired or involved in education.

The data analysis shows that around 23.1 percent of the sample are entrepreneurs in Mexico, while 65.2 percent are employed. Due to the unavailability of data on individual level social transfers to the non-employed, in the robustness check I choose the social benefit in the model such that the model implied entrepreneurship rate is equal to that in the data.

[1] Integrated Public Use Mico-data Series (IPUMS) International is conducted by the Minnesota Population Center, University of Minnesota, in an effort to deliver a database of harmonized census micro-data from around the world.

Figure B.1: The share of entrepreneurs within each bracket of riskiness of operating a business and entrepreneurial talent distributions



The equilibrium entrepreneurial talent (upper panel) and riskiness distributions (lower panel) are partitioned into 101 equidistant intervals. Then, for the population with entrepreneurial talents (riskiness) within a given interval, the share of entrepreneurs is calculated in the benchmark model, the models for Chile and Mexico. Higher intervals are associated with higher entrepreneurial talents and riskiness of operating a business.

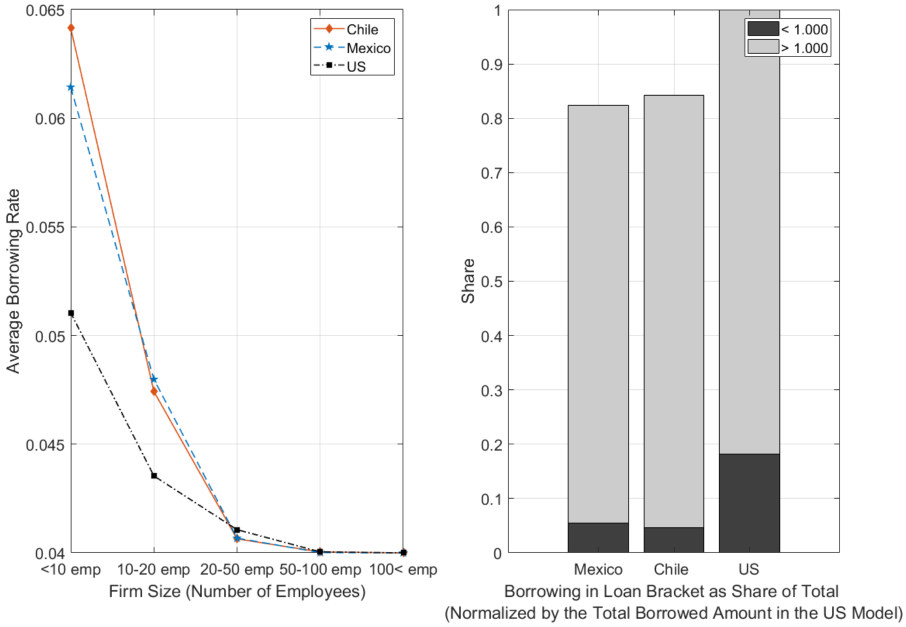
I then compare the model implied occupational and firm distributions, access to finance and output-labor ratio to the data.

To reach the entrepreneurship rate of 23.1% in the model, the social benefit needs to be set to 1.91 percent of the equilibrium wage, within the interval of average social benefit received by unemployed I find for Chile. The model implied labor market characteristics are compared with the data counterparts in table B.1.

Similar to the main results, the decrease in the social benefit leads to a lower employment rate, and the subsistence entrepreneurship rate goes up[2]. The composition of entrepreneurs is worse than the model implied compositions for Chile and US, as presented in Figure B.1. We can see that the share of entrepreneurs within the populations with higher entrepreneurial talents is increasing, and there is a threshold talent $\bar{z}$ above which everybody becomes an entrepreneur. This threshold is higher for the model of Chile and Mexico, in comparison to the benchmark model. In contrast, the share of entrepreneurs in the populations with higher riskiness of operating a business is decreasing in the benchmark model and

[2]It needs to be mentioned that the average share of necessity entrepreneurs in the US is 16% in GEM, while Fairlie et al. (2015) find that around 20% of entrepreneurs start-up from unemployment, which is a more objective measure of subsistence entrepreneurship (Fairlie and Fossen, 2018).

Figure B.2: Model implied access to finance by firm and loan size for Mexico, Chile and the US



The left panel illustrates the relationship between firm size and the average borrowing interest rate (in percent) in the model equilibria. The right panel plots the shares of capital borrowed in loans of size below $1 mln and above $1 mln. The total capital borrowed in the benchmark model is normalized to one. The total capital borrowed in the models for Chile and Mexico are relative to that in the benchmark model.

reaches zero relatively fast. This is not the case in the economies of Chile and Mexico, where the rate of decline is lower, and the share of entrepreneurs never reaches zero.

The resulting higher risk forces the lenders to charge higher borrowing interest rates, which further decreases the investment and affects the selection into entrepreneurship, as can be seen from Figure B.2 and the upper panel of Figure B.1 respectively. Even though total borrowing goes down, the share of borrowing of size lower than $1 mln goes up for the case of Mexico in comparison to Chile, but this is because the increase in entrepreneurship is mainly due to the entry of small entrepreneurs, and thus the SMEs borrow more in total.

Similar to the main results, the model predicts that the low social benefit in Mexico affects the resource allocations both in the labor and in capital markets. In particular, given that the unemployed agents cannot borrow to smooth consumption, and the social benefit is low, those with low assets are forced to transition to entrepreneurship instead of waiting for a job offer. This leads to resource misallocation in the labor market as entrepreneurs don't receive a job offer and thereby cannot directly transition to employment. Furthermore, the higher borrowing rates due to worsening of the composition of entrepreneurs affect the entry of middle skilled entrepreneurs and hinder investments, thus leading to capital misallocation.

As we can see from table B.2, the efficiency losses due to resource misallocation affect the output-to-labor ratio, which goes down by around 11.3 percent, larger than the decline

Table B.2: Comparison of model predicted moments with data for Mexico

variable	Model:Mexico	Data:Mexico
Y/L	88.73%	36.64%
$\Delta\tilde{r}$	4.40%	3.42%
Firm Distribution		
<5 emp	91.50%	89.70%
<10 emp	95.23%	95.50%
<50 emp	99.27%	99.10%

Note: The output-labor ratio Y/L - equilibrium output divided by the sum of employees and entrepreneurs, $\Delta\tilde{r}$ - borrowing interest rate spread (source: OECD, 2017). The firm distribution is presented as the fraction of firms below a given size (source: Busso et al., 2012).

for the case of Chile. Thus, only the occupational choice channel due to lower social benefit can explain around 17.8% of the difference in output-to-labor ratio between Mexico and the US. Furthermore, it predicts 4.4 percentage point spread between the borrowing interest rates of SMEs and large firms in comparison to the spread of 3.42% in the data and the model implied share of small firms is consistent with the data[3].

The robustness check shows that the model performance doesn't depend on the choice of the economy, and that the model can generate the relationship between the level of social benefits, entrepreneurship rates and access to finance for SMEs observed in the cross-country data.

B.2 Appendix

B.2.1 Calculation of Output-to-Labor Ratios

To calculate the output-to-labor ratios for Chile, Mexico and the US such that they are comparable with the model, I first need to calculate the share of employed in total population in each country. For these calculations, I use the National Socio-economic Characterization Survey for the year 2015 for Chile, the 2010 General Housing and Population Census for Mexico, and the 2015 Current Population Survey for the US. All databases are on the household level, and all members of the household are interviewed. The aim of these databases is to study the socio-economic characteristics of the general population in the respective country. In each data set, I can identify whether the individual worked for pay during the previous week of interview (employees and entrepreneurs) or not. Then, I calculate the

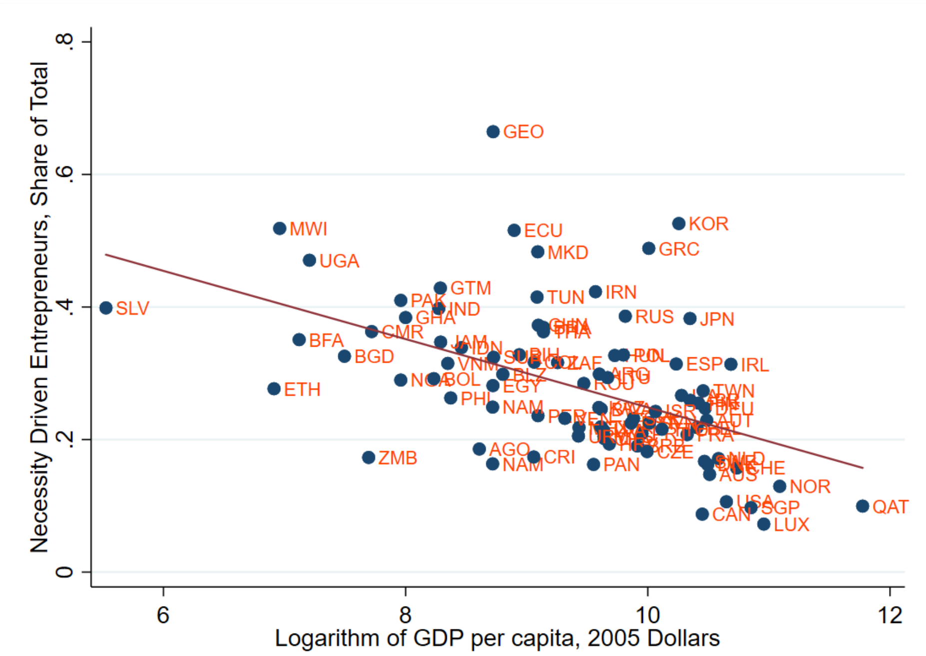
[3]Firm distribution moments for Mexico are taken from Busso et al. (2012).

share of employed in total population in each country, using weights when available. This measure tells which share of the total population in each country is directly involved in the generation of the value added.

I divide the GDP per capita of each country in constant prices by the share of employed (which also includes the entrepreneurs) to get the output-to-labor ratios. Finally, I calculate the output-to-labor ratios for Chile and Mexico as shares of that of the US. This gives the final result that the labor productivities in Chile and Mexico are around 37.8% and 27.4% of the labor productivity in the US.

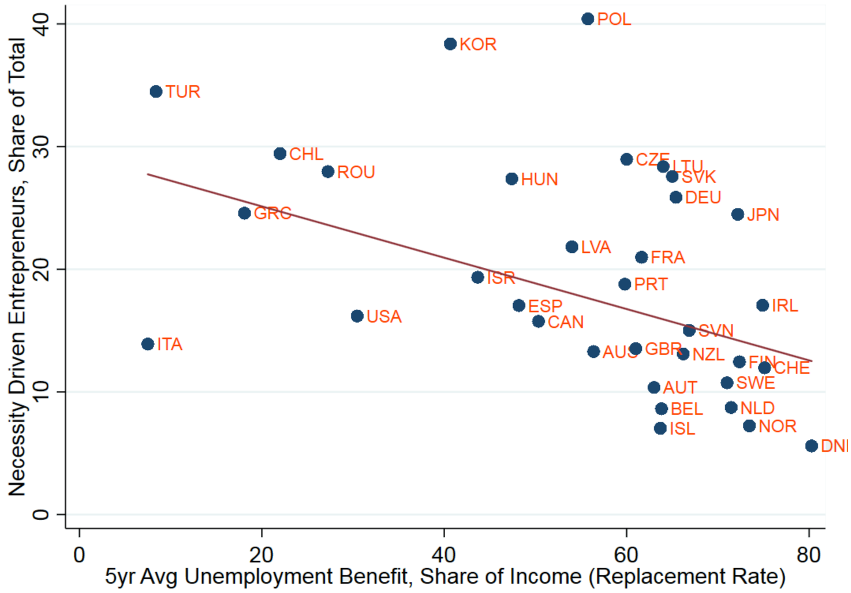
B.3 Appendix

Figure B.3: Share of necessity-driven entrepreneurs versus logarithm of GDP per capita



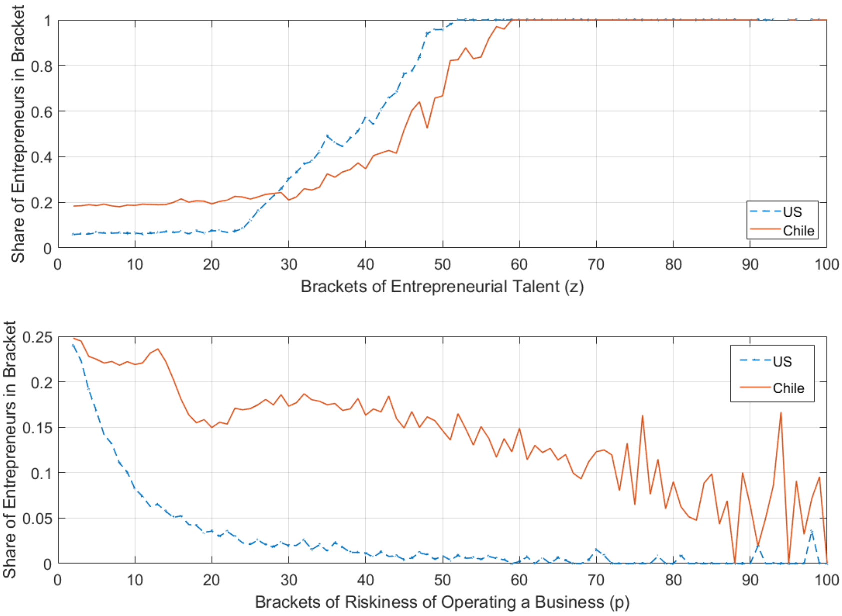
Sources: GEM Adult Population Survey. The share of necessity driven entrepreneurs is defined as the share of people within all entrepreneurs, who say they became entrepreneurs because they had no better choices of work (Average for years 2010-2014). The GDP per capita is in constant 2005 dollars (Source: Penn World Tables, 2011).

Figure B.4: The Share of Necessity Driven Entrepreneurs versus the 5yr Average Replacement Rate of UI



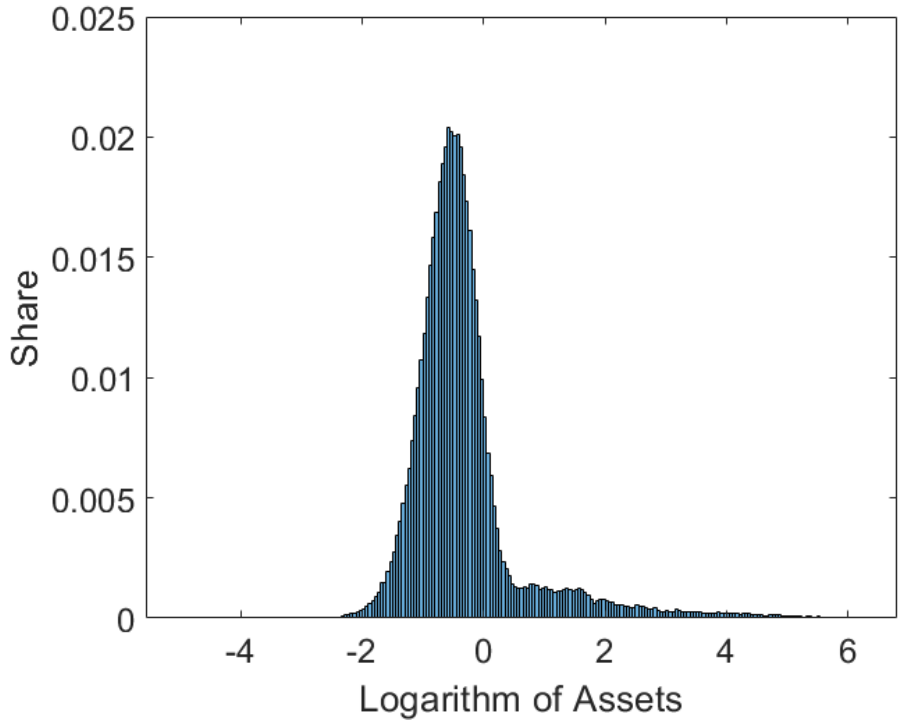
Sources: GEM Adult Population Survey. The share of necessity driven entrepreneurs is defined as the share of people within all entrepreneurs, who say they became entrepreneurs because they had no better choices of work (Average for years 2010-2014). The replacement rate of unemployment benefit is from OECD database.

Figure B.5: The share of entrepreneurs within each bracket of riskiness of operating a business and entrepreneurial talent distributions



The equilibrium entrepreneurial talent (upper panel) and riskiness (lower panel) distributions are partitioned into 101 equidistant intervals. Then, for the population with talents (riskiness) within a given interval, the share of entrepreneurs is calculated in the benchmark model, and the model for Chile. Higher intervals are associated with higher entrepreneurial talents and riskiness of operating a business.

Figure B.6: The logarithm of the asset distribution in the benchmark model



B.4 Appendix

B.4.1 Computational Approach

I solve the model using the value function iteration technique on the $Z \times A \times P$ state space, where Z, A and P are the entrepreneurial talent, asset, and riskiness of operating a business grids. The individual's value function is not concave, therefore her problem is solved on a grid that is much finer than the grids for the state variables. I use linear interpolation to calculate the value functions between grid points. The optimal saving problem is solved using the binary search method, augmented with a stage where the optimal point is compared with its neighboring grid points, to avoid capturing local maxima. The signaling game between the lenders and the entrepreneurs can have multiple Perfect Bayesian Equilibria that depend on the off-equilibrium beliefs. Following Athreya et al. (2012), I concentrate on the equilibrium that leads to the largest amount borrowed. Therefore, the model needs to be solved according to a specific algorithm presented below:

1. Choose initial tax and wage $\{w, T\}$,

2. Choose initial borrowing interest rate schedule, where the value of $r(x, J)$ in the first iteration is the risk-free rate, x is the loan grid, J is the sector.

3. Calculate the value and policy functions using value function iteration:

   (a) Start with a guess of the next period value functions $W(z', a', p)$, $N(z', a', p)$, $\mathbb{E}[S(z', a', p)|p]$, $\mathbb{E}[B_0(z', a', p)|p]$ and $\mathbb{E}[B_1(z', a', p)|p]$,

   (b) Using these value functions, find the optimal next period occupations and beginning of period value functions $V_{e=i,g=j}(z', a', p)$, calculate today's continuation values,

   (c) Given today's continuation values, calculate the optimal c & a' for $W(z, a, p)$, $N(z, a, p)$, $S(z, a, p, \epsilon)$, $B_0(z, a, p, \epsilon)$ and $B_1(z, a, p, \epsilon)$,

   (d) Calculate $\mathbb{E}[S]$, $\mathbb{E}[B_0]$ and $\mathbb{E}[B_1]$, and in addition to W and N, use them as starting values in (b),

   (e) Iterate until the maximum of the changes in all value functions is lower than a given tolerance level,

4. Use the value functions to simulate N individuals for T periods, check whether the stationary distribution has converged,

5. Given the stationary distribution of entrepreneurs, calculate the total amounts borrowed and defaulted upon for each x in each sector J,

6. Calculate the interest rate for each x and J:

$$r'(x, J) = \frac{\sum_y \left[\mathbb{1}_{g'(y)=1}\mathbb{1}_{x(y,r(x,J))=x}\right]}{\sum_y \left[\mathbb{1}_{g'(y)=1}\mathbb{1}_{x(y,r(x,J))=x}\right](1 - \sum_\epsilon D(y, x, r(x, J), \epsilon)Pr(\epsilon|p))} - 1$$

   If the demand for grid point x' is 0, assume $r(x', J) = r(x^+, J)$,where x^+ - first grid point to the right of x' ($x' < x^+$) that is actually borrowed[4],

7. Substitute $r(x, J) = \Upsilon r'(x, J) + (1 - \Upsilon)r(x, J)$ in (2) with updating parameter very low[5], and iterate until the financial market clears,

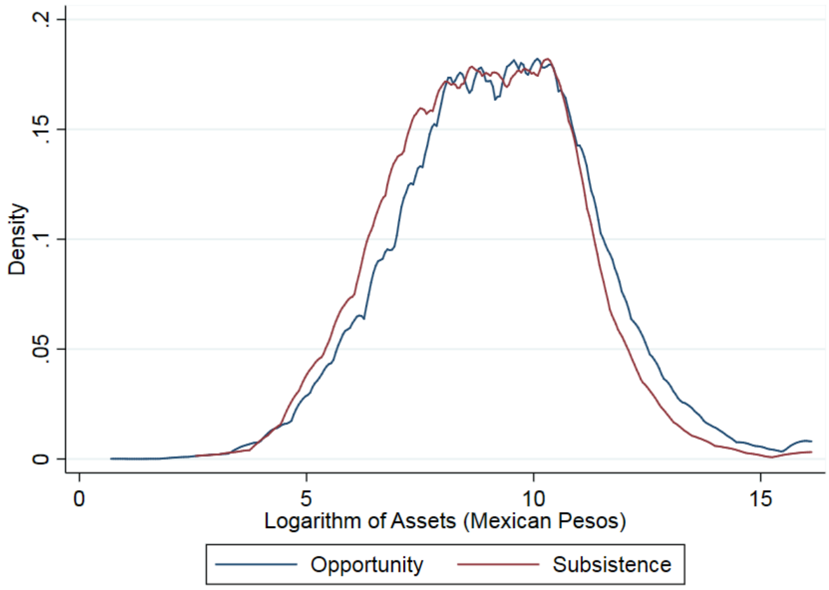
8. Update w, T in (1), given equations (3.21) and (3.22) and iterate until the labor market clears and the government budget is balanced.

[4]I assume that the off equilibrium beliefs of the lenders are the most optimistic, given the distribution of the entrepreneurs. The lenders believe that if someone had borrowed x', her probability of default would have been the default probability of the next highest amount x^+ that is actually borrowed. This method leads to the highest possible borrowing, because borrowed amount is negatively correlated with default probability in the model, and thereby borrowers of higher amounts will face lower interest rates.

[5]In the model solutions I choose the updating parameter $\Upsilon = 0.015$.

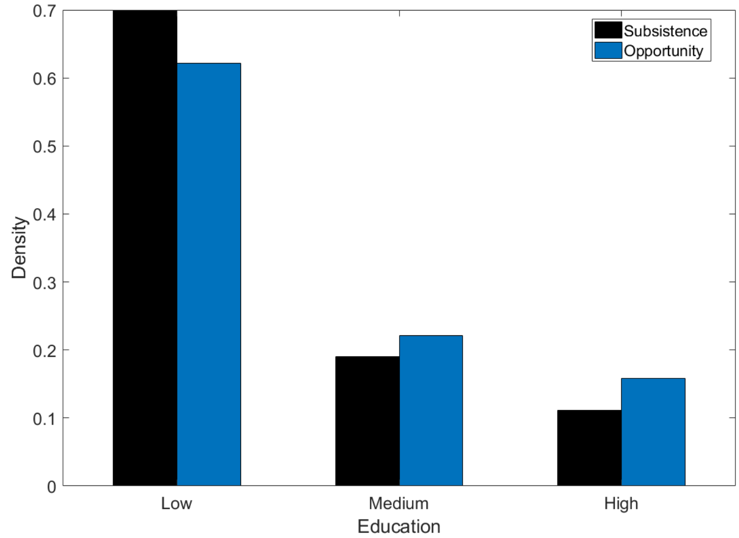
B.5 Appendix

Figure B.7: The logarithm of the asset distributions of opportunity and subsistence entrepreneurs in Mexico



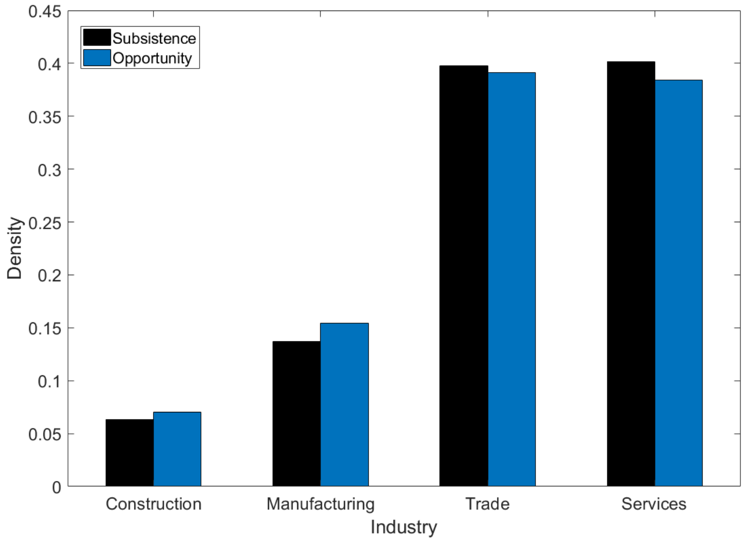
Data: National Survey of Mexican Micro-enterprises (ENAMIN), 2012. Entrepreneurs are defined to be subsistence, if to the question why they started the firm, their answer was one of the following: (i) 'This was the only way to earn income', (ii) 'The jobs I found were poorly paid', (iii) 'I didn't have other job opportunities'. The entries with zero or negative assets are dropped.

Figure B.8: The educational distribution of opportunity and subsistence entrepreneurs in Mexico



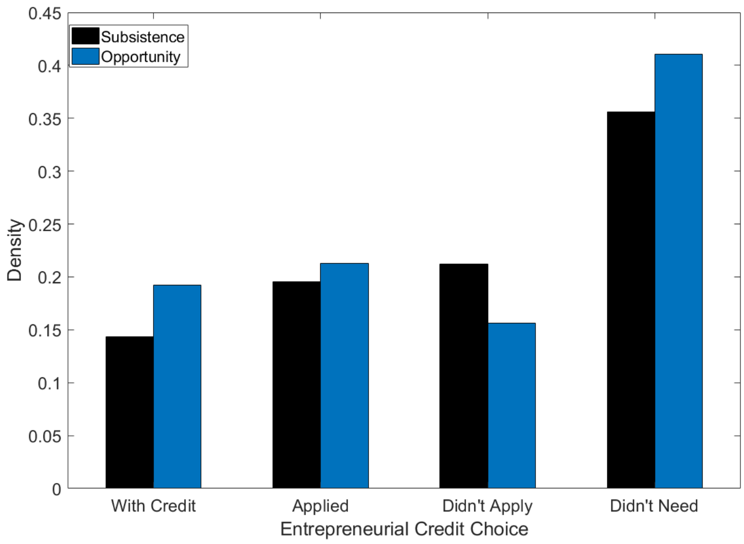
Data: National Survey of Mexican Micro-enterprises (ENAMIN), 2012. Entrepreneurs are defined to be subsistence, if to the question why they started the firm, their answer was one of the following: (i) 'This was the only way to earn income', (ii) 'The jobs I found were poorly paid', (iii) 'I didn't have other job opportunities'. People with at most secondary education are considered low educated, those with technical education - medium educated.

Figure B.9: The industry distribution of opportunity and subsistence entrepreneurs in Mexico



Data: National Survey of Mexican Micro-enterprises (ENAMIN), 2012. Entrepreneurs are defined to be subsistence, if to the question why they started the firm, their answer was one of the following: (i) 'This was the only way to earn income', (ii) 'The jobs I found were poorly paid', (iii) 'I didn't have other job opportunities'.

Figure B.10: Loan application activity of subsistence and opportunity entrepreneurs in Mexico



Data: National Survey of Mexican Micro-enterprises (ENAMIN), 2012. Entrepreneurs are defined to be subsistence, if to the question why they started the firm, their answer was one of the following: (i) 'This was the only way to earn income', (ii) 'The jobs I found were poorly paid', (iii) 'I didn't have other job opportunities'. The bars represent the shares of entrepreneurs within the subsistence and opportunity sub-groups. The bars 'With credit' are the share of the people who said they had a loan at the time of the survey. The bars named 'Applied' present the shares, who applied for credit during the last year, and the bars named 'Didn't Apply' visualize the shares, who didn't apply for credit during the previous year, because they were afraid they would be rejected. Finally, the bars labelled 'Didn't Need' indicate the share of entrepreneurs within sub-groups of subsistence and opportunity entrepreneurs, who didn't apply for credit because they didn't need one.

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Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig angefertigt und mich keiner anderen als der in ihr angegebenen Hilfsmittel bedient zu haben. Insbesondere sind sämtliche Zitate aus anderen Quellen als solche gekennzeichnet und mit Quellenangaben versehen.

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