Carnegie Mellon
Tepper
SCHOOL OF BUSINESS

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY
ECONOMICS

Titled

"ESSAYS ON MACROECONOMICS"

Presented by
Abha Kapoor

Accepted by

Laurence Ales 4/23/16

Chair: Prof. Laurence Ales **Date**

Approved by The Dean

Robert M. Dammon 5/5/16

Dean Robert M. Dammon **Date**

ESSAYS ON MACROECONOMICS

by

ABHA KAPOOR

Dissertation submitted to Carnegie Mellon University

in Partial Fulfillment of the requirements for the Degree of

Doctor of Philosophy

in Economics

April 2016

Dissertation Committee

Professor Laurence Ales (Chair)

Professor Stefano Sacchetto

Professor Sevin Yeltekin

Professor Emilio Osambela

This thesis is dedicated to Jyoti Kapoor (my Mum) and Vicky Kapoor (my Dad), for their unconditional love and support.

Abstract

Economists have thought very deeply about why productivity varies across firms and across countries. Complementary to this are the industry projects published by consultancy firms which identify several frictions faced by firms in developing countries. These frictions generate misallocation, as resources (like capital, labor) are not directed to the most productive firms of the economy. In my dissertation, I focus on analyzing the adverse effects of capital, labor market and behavioral frictions on firm/entrepreneurial growth and welfare. I use both a quantitative model-based approach and firm-level data from a large, developing country to understand this theory deeper. Through my research, I show that corporate diversification strategies, over-borrowing are adequate mechanisms to reduce the effect of these frictions.

In the first chapter, I determine whether the organizational structure of firms alleviates the effect of capital market frictions in developing countries. In this paper, I empirically and theoretically establish that capital misallocation is lower across business-group firms than across stand-alone firms. Business groups are an important organizational structure in most developing countries. I first propose a method which extends the identification approach of Hsieh and Klenow (2009) to a dynamic framework and structurally identifies mean investment distortions from firm-level data. I apply this scheme on a panel of manufacturing firms in India. I find that for most industries, mean investment distortions are lower for business-group firms than stand-alone firms and are increasing with firm size. Business-group firms also display lower cross-sectional dispersion in capital revenue productivity (marginal product of capital) over the entire sample period. In order to interpret these findings, I develop and estimate a two-sector model of firm dynamics in which firms choose their organizational structure, face investment irreversibility and financing frictions. Using the model, I show that capital reallocation and cashflow diversification within business groups translate into lower investment distortions and lower dispersion for group-affiliated firms.

In the second chapter, using cross-country data for 45 countries, I show that business group firms are more prevalent in countries with more stringent job protection provisions. This relation is robust to the inclusion of country-level governance, financial development indicators, hiring costs and other potential determinants of business group formation. To reconcile these empirical findings, I propose a general equilibrium model of firm dynamics in which firms choose their optimal employment policies and their decision to form a business group. I calibrate the model using realistic parameter values and study the effect of two types of job protection policies on the stationary equilibrium: (i) size independent and (ii) size dependent firing costs. I

find that these policies generate large labor misallocation and significant effects on aggregate variables: a firing tax which is equal to 1 years wage reduces aggregate output by 4-5 percent and aggregate labor by 5-8 percent. I also find that size-independent firing costs have greater distortionary effects on aggregate variables.

In the third chapter, I analyze the distortionary effect of time inconsistent preferences on the investment behavior of poor entrepreneurs. The specific form of time inconsistency that I consider is the quasi-hyperbolic discounting structure. I develop a model in which an entrepreneur is characterized by her degree of present bias i.e. her quasi-hyperbolic discount factor and chooses to execute a lumpy investment decision by borrowing from a Micro Finance Institution (MFI). Using the model I show that if the entrepreneur is sufficiently patient and if her project generates high returns, she optimally borrows and invests. However, if she is impatient and her project returns are modest then she is seen to undergo preference reversals and uses the microcredit for consumption rather than investment. Given this sub-optimal behavior, a non-profit MFI can prompt the impatient borrower to invest by allowing her to overborrow and offering her a larger loan size. This analysis suggests that larger, more flexible loan sizes can increase the take-up rate of micro-credit and build commitment for sophisticated, poor entrepreneurs.

Acknowledgement

There are several people who I would like to acknowledge and who have played a pivotal role in guiding me throughout my doctoral degree. This journey would not have so memorable and fulfilling without their assistance.

Firstly I would like to extend my heartfelt gratitude to Professor Laurence Ales for his invaluable insights and support. He has always encouraged me to approach research questions in economics from new perspectives and be aware of the broader policy implications of macroeconomic research. He has helped me clarify and elegantly articulate the research objectives, themes and issues that I have sought to address in my dissertation. I have greatly benefited from the advice that he has offered me and continues to offer me with respect to my research studies and job search process.

I would like to thank Professor Stefano Sacchetto for holding innumerable meetings with me; referring me to important papers in the finance literature and helping me attain a much nuanced understanding of classical finance concepts. I am grateful for the careful and meticulous feedback that he has always provided on my research. I would like to express my appreciation to Professor Sevin Yeltekin who has always offered a lot of constructive suggestions and advice during the research process and job market preparation period. I would also like to thank Professor Emilio Osambela for participating as an external faculty reader on my thesis committee.

I am thankful to several other faculty members at Tepper School of Business especially Professor Ariel Zetlin-Jones, Professor Bryan Routledge, Professor Bennett McCallum, Professor Chris Telmer, Professor Finn Kydland, Professor Fallaw Sowell and Professor Yuroslav Kryukov for their valuable time and comments. I am grateful to each of the PhD student friends that I have made during these years. I would like to thank Lawrence Rapp for providing me unlimited administrative support and making my PhD life much easier over these years. His thoughtful organization of tea sessions and PhD student social interactions are something that I have enjoyed a lot and will definitely miss.

I am especially grateful to my family and friends for being so understanding and supportive throughout my research journey. I would like to thank my parents, Jyoti Kapoor and Vicky Kapoor, for their relentless support and encouragement. They have always been very patient with me and I owe all my professional and personal successes to them.

My husband, Saurabh Taneja, has been my constant sounding board. I have been fortunate to share the various rewards and frustrations of my doctoral challenges with him. I am fortunate to have my sister and brother-in-law, Shruti Behal and Karan Behal just a phone call away and their advice and humor have really helped me navigate the various issues that I faced during this journey. Finally, I would like to thank my uncles, Dr. Sanjiv Talwar and Kapil Talwar, for being the best kind of mentors. I have much to learn from them.

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Chapter 1

Capital Misallocation and Firm Organizational Structure

1.1 Introduction

"India's Kesoram Industries is a notable example, shifting 80 percent of its capital across businesses units over the seven years we studied. Up until 2005, the company focused most of its capital expenditures on rayon and cement. Beginning in 2007, however, it moved the majority of new investments to the tire business to capture the double-digit growth in India's automobile sector…This type of strategic reallocation, our research has shown, is correlated with higher total returns to shareholders over time." — Excerpt from *McKinsey Quarterly*[1]

Firms in developing countries face large market frictions. These frictions can lead to high misallocation of production factors between firms and hence, large reductions in aggregate TFP. Several papers (Banerjee and Duflo (2005), Hsieh and Klenow (2009), Bartelsman, Haltiwanger, and Scarpetta (2013)) provide evidence on misallocation being more severe within developing countries and quantify TFP gains, of about 50 percent, from reducing misallocation to the US based efficiency level.[2]

A parallel body of work documents the wide prevalence of diversified business groups in developing countries and determines the optimality of this organizational form.[3] Masulis, Pham, and Zein (2011) find that family-owned business groups control approximately 40 percent of the market capitalization in emerging countries such as Indonesia, Korea and Turkey. I use a sample of large manufacturing firms in India and observe that group-affiliated firms have substantial market share ranging from 53.6 percent in the manufacturing sector to about 33.6 percent in other sectors. Moreover, business groups are seen to display high degrees of scale and scope: the average group consists of 12 independent firms and operates over 6 two-digit

[1] "Parsing the growth advantage of emerging-market companies", Insights and Publications, *McKinsey Quarterly*, May 2012.

[2] Hsieh and Klenow (2009) estimate the distribution of TFPR and find it to be more dispersed for China, India. Alfaro, Charlton, and Kanczuk (2008) find poorer countries to have a firm size distribution that is more dispersed, less skewed. Bartelsman, Haltiwanger, and Scarpetta (2013) compute the covariance between firm labor productivity and firm size and find it to be lower for the East European countries.

[3] Here, business groups are defined as a collection of independent firms that are linked together by informal (family, social) ties or formal (equity) ties.

industries.

Motivated by these two strands of literature, this paper investigates whether misallocation is lower for firms affiliated to business groups. To address this question, I pursue two strategies. I first, use firm-level data from the Indian manufacturing sector and empirically establish that production factors are misallocated to a lesser degree for business-group firms. Mean investment distortions are smaller for large business-group firms than large stand-alone firms. The cross-sectional dispersion in capital revenue productivity (marginal product of capital) is consistently smaller for business-group firms throughout the sample period. The lower mean and lower dispersion, suggests that business-group firms face less market frictions which results in better allocation of resources amongst them. I then develop a two-sector model of firm dynamics in which firms choose their organizational structure and productive capital while facing investment irreversibility and financing frictions. This model endogenously generates investment distortions and a distribution of stand-alone and business-group firms and is used to interpret the above empirical findings. I estimate the model using various moments computed from Indian-firm level data and demonstrate that investment distortions will be lower for group-affiliated firms due to capital reallocation and cash flow diversification options available within business groups.

Starting from the influential work of Banerjee and Duflo (2005), Hsieh and Klenow (2009), a rapidly growing literature attempts to understand the nature and reasons underlying the large misallocation of factors within developing countries. While one set of studies identifies the type of firms that face the most obstacles in their growth and development. Another set of studies, evaluates which frictions: business uncertainty, financing constraints, rigid labor regulations and others - are most severe and can account for the most amount of misallocation.[4]

In spite of business groups being an important organizational form in developing countries, their effect on firm-level misallocation remains an open empirical and theoretical question. This paper addresses this gap in the literature. There are two primary views with respect to business groups. According to the 'bright side', groups are welfare improving who substitute for the missing economic institutions of countries and facilitate firm growth (Leff (1978), Khanna and Palepu (2000)). Alternatively, the 'dark side' views group controlling shareholders as rent seeking agents who block new technologies, expropriate minority investors and hinder economic development Morck, Wolfenzon, and Yeung (2004). From a policy perspective, it is important to determine which of these two views dominates, so that government regulations in developing countries can either encourage the expansion of business groups or prescribe their elimination.

In the first section of the paper, I develop a simple method that identifies the mean distortions faced using firm-level or plant-level data. This method extends the identification approach of Hsieh and Klenow (2009) to a dynamic framework. Similar to their framework, I embed permanent firm-specific distortions in a heterogeneous firm investment model and infer the underlying distribution of the distortions by linking the model's first order conditions to observed firm variables. In contrast to their static framework, firm productivity follows a stochastic, persistent process and the reduced-form distortions affect firm's capital accumulation

[4]Asker, Collard-Wexler, and De Loecker (2014), Midrigan and Xu (2014), Buera, Kaboski, and Shin (2009), Lagos (2006), Bloom and Reenen (2010) argue that these frictions create wedges in the marginal product of factors between firms and this prevents factors from being allocated to the most efficient firms of the economy.

decisions. I show that when capital is a dynamic factor for firms and productivity is stochastic then, both distortions and productivity shocks generate dispersion in capital revenue productivity i.e. capital 'misallocation'. And therefore, a structural estimation approach needs to be employed to disentangle the effect of investment distortions from productivity shocks.

I then employ this identification scheme on a panel dataset of firms that belong to the Indian manufacturing sector over the period 1995 to 2013. The main findings from this analysis are: (1) Mean investment distortions are larger for large stand-alone firms than large business-group firms. The difference in mean investment distortions between large stand-alone firms and large business-group firms is on average 7 percent and for the entire firm sample it is on average 2 percent. I ensure that this relation is unaffected by the level of the concentration within an industry and find the estimated mean investment distortions to be larger for stand-alone firms in most 2-digit industries. (2) Using both unbalanced and balanced samples of data, I compute within-industry cross-sectional dispersion in capital revenue productivity and trace out its dynamics over the sample period. I show that dispersion measures for business-group firms, are consistently larger than those for stand-alone firms over the entire sample period. While the average value of dispersion is 0.79 for stand-alone firms it is 0.73 for business-group firms. These differences and large dispersion values also provide support for the claim that the Indian manufacturing sector saw minimal improvement in spite of industrial deregulation reforms. (3) Apart from looking at the firm organizational structures, I also find firm size to be a determining factor for investment distortions. I confirm Hsieh and Olken (2014)'s findings of mean distortions (i.e. capital revenue productivity ratios) increasing with firm size. In comparison to the smaller firms, the mean investment distortions for the largest Indian firms are almost double. This suggests that the largest, not the smallest firms in India face more obstacles in their growth and development. (4) In addition to these patterns for investment distortions, I compute the organizational distribution of firms across different sizes. I observe that stand-alone firms are more likely to be small; they constitute 87 percent of the total fraction of small firms and a much lower 35 percent of the total fraction of large firms.

In the second section of the paper, I construct a theoretical model that accounts for the above empirical patterns of capital misallocation. I develop a partial equilibrium model of an infinite horizon economy which is composed of two industries and a continuum of heterogeneous firms. In every period, firms receive their industrial productivity shocks and choose their organizational structure i.e. diversification state. Like the model frameworks in Maksimovic and Phillips (2002) and Gomes and Livdan (2004), the firms that produce goods of a single industry are referred to as stand-alone firms whereas diversified firms are referred to as business-groups. Firms operate a decreasing returns to scale production function and can accumulate productive capital over their lifetime. Within this model, I embed two capital market frictions that have been referred as the most important in shaping firm investment decisions: capital adjustment costs and financing frictions. Capital accumulation by firms is irreversible and associated with convex adjustment costs. This feature is consistent with observations in Indian firm-level data: there is significant inertia and asymmetry associated with firm investment. Additionally, financial market imperfections are formulated in this economy by assuming that firms can issue finance to fund their operating costs and factor payments. However, external financing is costly and associated with reduced-form proportional costs similar to the approach of Hennessy and Whited (2007), Gomes (2001).[5]

This model is structurally estimated so that it can match the above patterns of investment distortions and various empirical moments of investment and external financing for firms in India. To estimate the underlying model parameters, an Indirect inference approach is used. The estimated parameter values are those which minimize the distance between the empirical moments and the corresponding simulated model moments.

I obtain the following three results. Firstly, the self-selection channel in the model predicts that gains from diversification are the highest when firms receive similar or a higher productivity shock in the other industry. This further implies that stand-alone firms do not form business groups as they receive asymmetric productivity shocks (a lower productivity shock in the other industry). Here, the firm-level production function exhibits decreasing returns to scale which bounds firm growth in any industry and causes firms to diversify.

Secondly, I show that business-group firms benefit from the internal capital reallocation option when external reallocation is infinitely costly. We know that when production uncertainty is high and investment is irreversible, firms are *ex-ante* more cautious about investing as the disinvestment option will be unavailable to them in the future (user-cost effect) (Abel and Eberly (1999), Bertola (1998)). This cautious behavior results in firms investing less than the frictionless scenario and creates wedges/distortions in the investment Euler equation. I use simulated data from the model for several (productivity) uncertainty values, to show that business groups are less likely to face a binding investment irreversibility constraint. This implies that ex-ante, business groups face a lower user-cost effect and therefore, their investment distortions do not increase a lot. Stand-alone firms however, are more likely to face a binding irreversibility constraint which implies a higher user cost effect and higher mean investment distortions.

Thirdly, I show that high costs of external finance are more likely to affect the investment/growth decisions of stand-alone firms. Cashflows are diversified within business groups which reduces their reliance on costly external funds. Self-selection also implies that they are on average larger than stand-alone firms and hence, generate more internal funds. Stand-alone firms are more likely to be constrained in the economy as they are more likely to use external funds. Therefore, higher costs of finance disproportionately increase the mean investment distortions for stand-alone firms than business-group firms. Due to the strategic advantages within business groups, dispersion in capital revenue productivity is also smaller for business-group firms.

In the model, the standard deviation of industrial productivity shocks is a key parameter which determines the benefit of the capital reallocation and cash flow diversification options available within business groups. When uncertainty is low, both the user cost effect and a stand-alone firm's requirement for external funds is low. Therefore, mean investment distortions are higher only for a small fraction of stand-alone firms. As productivity uncertainty increases, the real options effect on a stand-alone firms investment is greater. These firms are

[5]The model analysis and results do not get altered significantly, if it is instead assumed that investment is partially reversible

inactive more frequently as the disinvestment option is unavailable to them in the future. High uncertainty also increases the riskiness of firm cashflows for stand-alone firms, which increases their requirement for external funds.

Finally I show that the model can also generate a slight increasing relation between mean investment distortions and firm size. Larger firms i.e high revenue firms have larger investment opportunities and as they use more external funds, higher financing costs distort their investment decisions to a greater extent (Midrigan and Xu (2009)). I find that mean investment distortions are increasing with firm size for stand-alone and business-group firms.

Related Literature

My paper contributes to the literature in several important ways. Firstly, a large number of papers identify whether and to what extent factor misallocation varies across different firm dimensions - firm size, industries, public versus private ownership. For instance, Garicano, LeLarge, and Reenen (2013) and Hsieh and Olken (2014) find firm size to be a determining factor. Alfaro and Chari (2014) study the effect of deregulation policies in India. They find evidence for higher firm entry rates, higher growth rates of large incumbent firms and a shrinking middle in the deregulated industries. Relative to the existing work, in addition to firm size, I also emphasize on variations in factor distortions between business-group firms and stand-alone firms.

This paper is also related to the vast number of works that study the underlying effects and consequences of firm diversification decisions. In contrast to the view for US conglomerates, it is largely believed that diversified business-group firms perform better than stand-alone firms in developing countries. Khanna and Palepu (2000), Claessens, Djankov, Fan, and Lang (2003) document larger Tobin's Q, profitability ratios for public business-group firms. While they study differences in firm value between these two types of firms, I employ a different approach and focus on empirically observed differences in factor misallocation measures. They restrict their analysis to public firms and do not study private firms. I correct for this selection bias as private firms comprise a significant fraction of the total firm sample in most developed and developing countries and hence, excluding them might give inconsistent results.

As pointed out by Maksimovic and Phillips (2002), Gomes and Livdan (2004), measurement error and endogeneity of firm diversification may also confound the diversification premium results in the above papers. Therefore, I develop a model that allows firm organizational structure to be endogenous, incorporates capital market imperfections. I use the model to give support to my empirical findings and show that it is the higher organizational flexibility of business groups which produces lower investment distortions, lower capital misallocation for business-group firms.

The remainder of the paper is organized as follows. Section 2 provides empirical evidence on misallocation across Indian firm sizes and organizational structures. Section 3 outlines a simple dynamic theoretical model of heterogeneous firms which endogenously generates capital misallocation across firms and a stationary distribution of stand-alone and business-group firms. Section 4 and 5 describe the decision rules of agents in the economy, the estimation procedure used and the model results. Section 6 concludes.

1.2 Identification of Capital Misallocation

In this section, I sketch a dynamic model of heterogeneous firm production that will enable me to empirically identify whether investment market frictions vary by firm organizational structure. I then briefly discuss the source of firm-level data that I use and present evidence on the distortions faced by stand-alone and business-group firms in India while controlling for their size and industry.

The economy consists of a continuum of firms who produce their differentiated goods and make optimal factor decisions each period. Firms are heterogeneous with respect to their productivity shocks and face investment distortions each period. Investment distortions are specific to the firm and increase/decrease the price of capital for the firm. The above model setup shares some similarities with those analyzed by Hsieh and Klenow (2009), Restuccia and Rogerson (2008) with some important differences. Like Hsieh and Klenow (2009), I assume that each firm at the beginning of time draws an idiosyncratic cost of capital i.e. an investment distortion. This distortion permanently affects its investment decisions at each stage of its lifecycle i.e. firm growth is affected. In contrast to their work, I aim to identify distortions from a panel of firm-level data and therefore, consider a dynamic framework and assume capital to be a dynamic factor for firms.

In the static version of the model, distortions are the only cause for capital misallocation and hence, they can be easily identified using the model's first order conditions. However, in a dynamic framework, I show that both productivity uncertainty and investment distortions generate capital misallocation. I then use structural estimation to identify the underlying distribution for productivity shocks and investment distortions.

1.2.1 A Model with investment distortions

Consider an economy that consists of S manufacturing industries. Each industry s consists of a continuum of firms of measure 1. Firms in each industry differ according to their organizational structure; firm i within this industry s can either be a stand-alone firm or a business-group firm (SA or BG). If firm i belongs to the set of stand-alone firms then, $i \in [0, M_s]$. Else, if firm i is a business group then, $i \in [M_s, 1]$.

For identification of firm distortions, I take the organizational structure of the firm as given. Firms report their structure in the data and I compute distortions across different firm structures. Then M_s is the fraction of business-group firms as reported in the data in industry s.[6]

Firms enter each period, observe their idiosyncratic productivity Z_{si} and produce revenue using their accumulated capital stock K_{si} and by hiring labor L_{si}. Production occurs via a decreasing returns to scale technology and firm-revenue is given by,

$$R_{si} = Z_{si}(K_{si}^{\alpha_{ks}} L_{si}^{\alpha_{ls}}) \tag{1.1}$$

[6]In the second section of the paper, I address the endogeneity issue by including the selection margin in a heterogeneous firm investment model. In this model, firms choose their asset holdings and their organizational form i.e. whether they want to operate as stand-alone or business-group firms.

Assumption 1. *Capital and labor share parameters $\alpha_{ks} < 1, \alpha_{ls} < 1$ can differ across industries but, are identical for firms that belong to industry s.*

Assumption 2. *Let Z_{si} follow a discrete-time autoregressive process of order 1 with underlying parameters $(\rho^t_{Zs}, \sigma^t_{Zs})$ which depend on industry s and type $t \in \{SA, BG\}$ of firm i and $0 < \rho^t_{Zs} < 1$,*

$$log(Z'_{si}) = \rho^t_{Zs} log(Z_{si}) + \epsilon_{Zsi} \qquad , \epsilon_{Zsi} \sim^{i.i.d.} \mathbb{N}(0, (\sigma^t_{Zs})^2) \tag{1.2}$$

Assumptions 4 and 2 are associated with firm production technology. According to these assumptions all firms in industry s are characterized by the same production technology and draw persistent productivity shocks from an ergodic distribution. While these assumptions might be restrictive, they are commonly used in this literature. Note that if there was heterogeneity in factor shares and demand shocks within industry s, then, this would also generate wedges in the first order conditions and these would be mismeasured as distortions. In my empirical analysis, I also compute the mean distortions between similarly-sized stand-alone and business-group firms. This should control for this measurement bias, as technological differences are more likely to arise between large and small firms instead of across similarly-sized firms within industry s.

In the above specification, I consider firm productivity to follow a persistent AR(1) process and do not allow for permanent productivity differences between firms. Alternatively, one can develop a model in which firms have a productivity fixed effect in addition to the AR(1) process and estimate firm-level investment distortions process using this model. I find that estimated distortions do not change in value when considering this alternative model.[7]

Although labor is a static factor for the firm, capital investment has the time-to-build feature. Firms can use their productive capital only in the following period. The law of motion of capital accumulation is given by,

$$K'_{si} = I_{si} + (1 - \delta) K_{si} \tag{1.3}$$

In the above equation, I consider economy-wide capital and labor to be composite goods that are employed by all firms and industries in production. In other words, all capital goods and workers of firm i in industry s (equipments, structures, tools etc.) are referred by the single variables K_{si} and L_{si} respectively. Since, I do not allow for different types of capital, the economic depreciation on capital δ is also assumed to be identical across all firms and and across all manufacturing industries.[8] (Henceforth, all future values of variables are denoted by primes.)

In this economy, firms in every period face investment distortions only and I now provide more details on how I characterize these investment distortions.[9]

[7] Although the introduction of permanent productivity differences between firms will enable us to match certain empirically observed moments better, like the dispersion in log revenue, size distribution of firms and others. However, these fixed effects will not affect firm-level capital productivity ratios and hence, result in the same estimated values for investment distortions process.

[8] While the composition of capital goods is likely to be important both at the firm-level and the industry-level, I follow much of the economics literature while making this simplifying assumption.

[9] In this paper, I focus only on capital misallocation and the identification of firm-level investment distortions from Indian panel-data. Applying the technique of Hsieh and Klenow (2009) to my panel dataset, I too find

Assumption 3. *Each firm i within industry s and of type $t \in \{SA, BG\}$, begins its lifecycle by drawing a permanent distortion τ_{Ksi}. I assume that distortions τ_{Ksi} follow a log-normal distribution with underlying parameter mean 0 and standard deviation σ^t_{Ks} which depends on industry s and type t. That is the underlying distribution is represented as,*

$$ln(1 + \tau_{Ksi}) \sim^{i.i.d.} \mathbb{N}(0, (\sigma^t_{Ks})^2) \tag{1.4}$$

In Assumption 5, distortions τ_{Ksi} is a reduced form way of representing all kinds of frictions that firms face in their capital markets and over their life cycle.[10] These distortions can depend on the organizational form of the firm. They can refer to adjustment costs, uninsurable investment risk, import tariffs on capital goods, constrained access to debt and equity or policy-related frictions such as size restrictions and others. I also assume here that firms do not face any frictions in their labor markets and labor market distortions are identically equal across firms. This assumption seems reasonable, because in the data I find that empirical measures of labor misallocation are significantly lower than measures of capital misallocation. In the later section of the paper, I explain how investment distortions can be generated endogenously via two frictions that affect firm investment decisions: adjustment costs and financing frictions.

With Assumptions 4, 2 and 5 specified, I now specify the dynamic programming problem for firm i.

Firm's Problem

If r is the exogenous real interest rate in the economy, then the dynamic programming problem for Firm i that belongs to industry s and type t is to maximize its lifetime profits and choose its investment I_{si}, labor input L_{si} given its state (Z_{si}, τ_{Ksi}). Here Z_{si} is firm's productivity shock and τ_{Ksi} is the permanent distortion that firm i faces while buying investment goods.

$$V(Z_{si}, K_{si}; \tau_{Ksi}) = \max_{I_{si}, L_{si}} \left[d_{si} + \frac{1}{1+r} \int V(Z'_{si}, K'_{si}; \tau_{Ksi}) dP_s(Z'_{si}|Z_{si}) \right]$$

where Firm i has firm-specific cost of investment P_{Ksi},

$$P_{Ksi} = P_K(1 + \tau_{Ksi}) \tag{1.5}$$

its budget constraint is,

$$d_{si} = Z_{si} K_{si}^{\alpha_{ks}} L_{si}^{\alpha_{ls}} - P_{Ksi} I_{si} - W L_{si} \tag{1.6}$$

evidence of both capital and labor misallocation across firms within India. Over the sample period 1995-2013, the within-industry dispersion in log capital productivity is 0.77 and the within-industry dispersion in labor productivity is 0.58. These statistics suggest that Indian firms face much higher constraints with respect to their investment rather than their labor accumulation decisions. In my other research work Kapoor (2016), I study and discuss identification of labor distortions across firms in India.

[10] To simplify the estimation procedure, I assume that the cross-sectional distribution for log distortions is such that the mean is equal to zero.

its capital stock evolves according to,

$$K'_{si} = I_{si} + (1-\delta)K_{si} \tag{1.7}$$

and its bounds on investment and labor inputs are,

$$K'_{si} > 0 \tag{1.8}$$

$$L_{si} > 0 \tag{1.9}$$

In the above value function, $P_s(Z'|Z)$ denotes the conditional distribution function for firm productivity given the current realization of firm's productivity shock. Also as the model operates in partial equilibrium, firms take the aggregate factor prices (P_K, W) as given and these are assumed to be fixed throughout the economy's lifetime.

Identification Equations

Since labor is a static factor for firms, we can reduce the above problem by optimizing out labor in each period. If firm i in industry s and of type $t \in \{SA, BG\}$ has state variables $(Z_{si}, K_{si}, \tau_{Ksi})$ then its profit function for the current period is,

$$\Pi(Z_{si}, K_{si}) = \max_{L_{si}} \left[Z_{si} K_{si}^{\alpha_{ks}} L_{si}^{\alpha_{ls}} - W L_{si} \right] \tag{1.10}$$

Solving for labor L_{si} in the above static optimization problem, I obtain a closed-form solution for the firm's profit function. We see that this profit function only depends on the firm's productivity shock Z_{si} and its accumulated capital K_{si},

$$\Pi(Z_{si}, K_{si}) = c_s \tilde{Z}_{si} K_{si}^{\theta_s} \tag{1.11}$$

Here constant $c_s = \left(\frac{\alpha_{ls}}{W}\right)^{\frac{\alpha_{ls}}{1-\alpha_{ls}}} (1-\alpha_{ls})$ depends on the labor share parameter α_{ls} and aggregate wage W. The transformed productivity shock $\tilde{Z}_{si} = Z_{si}^{\frac{1}{1-\alpha_{ls}}}$ depends on firm's productivity and curvature parameter $\theta_s = \frac{\alpha_{ks}}{1-\alpha_{ls}}$.

Using the above profit function, I now solve for the Investment Euler equation which determines the firm's optimal choice for its next period capital stock K'_{si}. I also show that the investment Euler equation can be used to identify the unknown parameters of the underlying distortion process.

Proposition 1. *If capital is a dynamic factor, investment distortions are permanent but heterogeneous across firms and follow a lognormal distribution with parameters depending on the underlying industry s and type t of firm i,*

$$ln(1+\tau_{Ksi}) \sim^{i.i.d.} \mathbb{N}(0, \sigma^t_{Ks})$$

then using the Euler equation we obtain,

1. *the firm-specific distortion acts as a tax on its capital accumulation choices,*

$$K'_{si} = \left[\frac{c_s\theta_s \tilde{Z}_{si}^{\rho^t_{Zs}} exp(\frac{(\sigma^t_{Zs})^2}{2(1-\alpha^2_{ls})})}{P_k(r+\delta)(1+\tau_{Ksi})}\right]^{\frac{1}{1-\theta_s}} \tag{1.12}$$

2. *the underlying volatility parameter of distortions σ^t_{Ks} is identifiable from the ensemble mean and standard deviation of the capital profitability series*

$$\frac{P_k(r+\delta)}{c_s\theta_s} e^{(\frac{(\sigma^t_{Ks})^2}{2})} = \mathbb{E}\left[\frac{\Pi'_{si}}{K'_{si}}\right] \tag{1.13}$$

$$\sqrt{\frac{(\sigma^t_{Zs})^2}{(1-\alpha_{ls})^2} + (\sigma^t_{Ks})^2} = Std\left[log(\frac{\Pi'_{si}}{K'_{si}})\right] \tag{1.14}$$

Proof. of (1):
Consider the Euler equation where investment decisions of firms are made at the intertemporal margin,

$$P_k(1+\tau_{Ksi}) = \frac{1}{1+r}\mathbb{E}_{Z'|Z}\left[c_s\theta_s Z_{si}^{'\frac{1}{1-\alpha_{ls}}} K_{si}^{'\theta_s-1} + (1-\delta)P_k(1+\tau_{Ksi})\right] \tag{1.15}$$

Note that in the above equation, the conditional expectation of next period's productivity shock depends on the current realization of productivity for firm i. Since, distortions are permanent draws for the firm the above equation can be rearranged as,

$$P_k(r+\delta)(1+\tau_{Ksi}) = \mathbb{E}_{Z'|Z}\left[c_s\theta_s\frac{\Pi'_{si}}{K'_{si}}\right] \tag{1.16}$$

where Π'_{si} denotes firm's profits after paying out labor and other material costs. In contrast to a frictionless model of firm investment, we see that investment distortions can lead to under-accumulation/overaccumulation of capital i.e. they create wedges in the marginal product of capital. Firm chooses its next period capital stock by balancing the costs versus the benefits. In the above equation, the left hand side represents the marginal cost of capital which depends on the economy-wide price of capital (interest rate, depreciation rate) and the investment distortion which is the idiosyncratic cost of capital for firm i. The right hand side is the expected marginal benefit from capital accumulation which results in possibly higher profits for firm i in the next period.

From 1.17,

$$P_k(r+\delta)(1+\tau_{Ksi}) = \mathbb{E}_{Z'|Z}\left[c_s\theta_s\tilde{Z}'_{si}K_{si}^{'\theta_s-1}\right] \tag{1.17}$$

we can take K'_{si} out of the conditional expectation,

$$P_k(r+\delta)(1+\tau_{Ksi}) = c_s\theta_s\mathbb{E}_{Z'|Z}\left[\tilde{Z}'_{si}\right]K_{si}^{'\theta_s-1} \tag{1.18}$$

and rearrange it to obtain a closed form solution for firm i's optimal choice for next period capital stock

$$K'_{si} = \left[\frac{c_s \theta_s \mathbb{E}_{Z'|Z} \left[\tilde{Z}'_{si} \right]}{P_k (r+\delta)(1+\tau_{Ksi})} \right]^{\frac{1}{1-\theta_s}} \tag{1.19}$$

Substituting for the AR productivity process for $\tilde{Z}'_{si}$ I obtain the final expression,

$$K'_{si} = \left[\frac{c_s \theta_s \tilde{Z}_{si}^{\rho^t_{zs}} exp(\frac{(\sigma^t_{Zs})^2}{2(1-\alpha^2_{ls})})}{P_k (r+\delta)(1+\tau_{Ksi})} \right]^{\frac{1}{1-\theta_s}} \tag{1.20}$$

In the absence of aggregate uncertainty, if firm-level investment distortions were identically equal to zero then the above equation predicts that firms would only adjust their capital stock according to their idiosyncratic productivity shocks received every period. Productive firms would expand more, whereas unproductive firms would sell their excess capital stock. Distortions however, behave as a tax or subsidy on these productivity realizations and generate misallocation across firms within the economy. □

Proof. of (2) and (3):
To identify investment distortions, I consider the actual realization of the capital profitability ratio for firm i in period $t+1$,

$$\frac{\Pi'_{si}}{K'_{si}} = \tilde{Z}'_{si} K'^{\theta_s - 1}_{si} \tag{1.21}$$

which can be written as,

$$\frac{\Pi'_{si}}{K'_{si}} = \frac{\tilde{Z}'_{si}}{\mathbb{E}_{Z'|Z} \left[\tilde{Z}'_{si} \right]} \mathbb{E}_{Z'|Z} \left[\tilde{Z}'_{si} K'^{\theta_s - 1}_{si} \right] \tag{1.22}$$

The expected marginal product of capital can be substituted for using the Investment Euler equation 1.18,

$$\frac{\Pi'_{si}}{K'_{si}} = \frac{\tilde{Z}'_{si}}{\mathbb{E}_{Z'|Z} \left[\tilde{Z}'_{si} \right]} \frac{P_k (r+\delta)(1+\tau_{Ksi})}{c_s \theta_s} \tag{1.23}$$

$$\frac{\Pi'_{si}}{K'_{si}} = \frac{exp(\frac{\epsilon_{Zsi}}{1-\alpha_{ls}})}{\mathbb{E}(exp(\frac{\epsilon_{Zsi}}{1-\alpha_{l}s}))} \frac{P_k (r+\delta)(1+\tau_{Ksi})}{c_s \theta_s} \tag{1.24}$$

In the above expression we see that the actual capital profitability ratio is a function of firm-specific investment distortion and the productivity shock which the firm realizes in period $t+1$. This result is different from the result that Hsieh and Klenow (2009) obtain using their static model. If capital is a static input in production, then any wedges in the capital profitability ratio would only be due to the permanent distortions that firms receive. Firms with higher capital profitability ratios would be identified as facing larger investment distortions whereas smaller distortions would imply lower profitability ratios for firms. In a dynamic investment model, productivity shocks also generate wedges in the capital profitability ratio. If a firm receives a higher than expected productivity shock, its already chosen capital would be inefficient in a static sense and a positive wedge would be created in the firm's capital profitability ratio. Therefore, a dynamic model predicts that productivity shocks can also generate capital 'misallocation'.

Taking unconditional expectations of the above equation and recognizing that firm-level productivity shocks and investment distortions are independent stochastic processes we obtain our second result,

$$\begin{aligned}\mathbb{E}(\frac{\Pi'_{si}}{K'_{si}}) &= \mathbb{E}(\frac{exp(\frac{\epsilon_{Zsi}}{1-\alpha_{ls}})}{)}\mathbb{E}(exp(\frac{\epsilon_{Zsi}}{1-\alpha_{l}s}))\frac{P_k(r+\delta)\mathbb{E}(1+\tau_{Ksi})}{c_s\theta_s} \\ &= \frac{P_k(r+\delta)\mathbb{E}(1+\tau_{Ksi})}{c_s\theta_s}\end{aligned} \tag{1.25}$$

For our third result, I take natural logarithm of equation 1.24,

$$log(\frac{\Pi'_{si}}{K'_{si}}) = \frac{\epsilon_{Zsi}}{1-\alpha_{ls}} - \frac{(\sigma^t_{Zs})^2}{2(1-\alpha_{ls})^2} + log(1+\tau_{Ksi}) + log(\frac{P_k(r+\delta)}{c_s\theta_s}) \tag{1.26}$$

When I take the standard deviation of the above expression, I obtain the third result which relates the unobserved parameters, volatility of productivity shocks σ^t_{Zs} and volatility of investment distortions σ^t_{Ks} to the dispersion in (log) capital profitability series,

$$Std\left[log(\frac{\Pi'_{si}}{K'_{si}})\right] = \sqrt{\frac{(\sigma^t_{Zs})^2}{(1-\alpha_{ls})^2} + (\sigma^t_{Ks})^2} \tag{1.27}$$

□

In the above identification equations, 1.25 and 1.27, the mean and standard deviation that appear are the ensemble mean and standard deviation of the capital profitability process. These moments are typically unobserved. The following proposition gives us a relation between unobserved ensemble moments and time series moments of firm's observed capital productivity ratio.

Lemma 1. *If the productivity process Z_{si} is ergodic stationary, distortions are i.i.d. across firms and the mean and standard deviation of the capital productivity ratio exist and are finite then, according to the Ergodic theorem, the time-series average of the capital productivity ratio converges almost surely to the ensemble mean of capital revenue productivity ratio,*

$$\bar{\mathbb{E}}^t_s\left[\frac{\Pi'_{si}}{K'_{si}}\right] \rightarrow_{a.s.} \mathbb{E}\left[\frac{\Pi'_{si}}{K'_{si}}\right] \tag{1.28}$$

and the sample standard deviation converges almost surely to the ensemble standard deviation of the capital revenue productivity ratio.

$$\bar{Std}^t_s\left[log(\frac{\Pi'_{si}}{K'_{si}})\right] \rightarrow_{a.s.} Std\left[log(\frac{\Pi'_{si}}{K'_{si}})\right] \tag{1.29}$$

Proof. Z_{si} is an AR(1) process with parameter $0 < \rho^t_{Zs} < 1$ which implies that it is a covariance stationary and ergodic process. Distortions τ_{Ksi} are permanent and i.i.d. across firms and hence, are strictly stationary. From the Euler equation, we see that the capital revenue productivity ratio is a function of these stationary shocks (firm-specific distortions and productivity). Therefore, if mean, variance and covariance of $\{(\frac{\Pi'_{si}}{K'_{si}})\}$ exists and are finite, then the capital profitability series is covariance stationary. I can also easily show that the auto-covariance function of this stochastic process decays towards zero. Then according to the Ergodic theorem, (Hamilton (1994)),

$$\frac{1}{T}\sum_{t=1}^{T}\frac{\Pi'_{si}}{K'_{si}} \rightarrow_{\text{a.s.}} \mathbb{E}\left[\frac{\Pi'_{si}}{K'_{si}}\right] \tag{1.30}$$

where the left hand side is the sample-mean capital revenue productivity ratio and it almost surely converges to the ensemble mean of the capital revenue productivity ratio for asymptotically large sample sizes. The same reasoning holds for convergence of the unobserved ensemble standard deviation to the time series sample of capital productivity ratio for approximately large sample sizes. □

Using the above methodology, identification equations 1.25, 1.27 and Lemma 1, I obtain a way of identifying firm-level (unobserved) investment distortions using (observed) time series sample mean and dispersion of firm-level capital profitability ratios. These moments can be used to empirically determine if firms operate in a frictionless environment in India or if there exist significant differences in distortions between stand-alone and business-group firms. If in the data, revenue productivity ratios are similar across firms then according to this methodology, the organizational structure of firms does not affect the market frictions faced by them.[11]

1.2.2 Data Description

Firm-level data for India is drawn from the Prowess database prepared by CMIE, Center for Monitoring the Indian Economy. This database records detailed financial, ownership and industry information on large public and private firms that operate within the formal Indian sector across a wide range of industries manufacturing, services, wholesale and retail trade. The firms included in the database account for more than 70 percent of industrial output, 75 percent of corporate taxes, and more than 95 percent of the excise taxes collected by the Government of India.

The advantage of using this database is that unlike the cross-sectional plant-level ASI (Annual Survey of Industries) database used in Hsieh and Klenow (2009), Prowess stores panel data on firms. This enables me to analyze growth at the firm-level and see how firm variables and ownership adjust over a long sample period. In contrast to most of the commonly used datasets in academic literature, (Compustat Global, Worldscope), the dataset covers a large fraction of private firms operating in the Indian economy. About two-thirds of the firms in the raw dataset consist of private firms. Finally, it tracks ownership information on firms and identifies the firms that belong to business-groups. This aspect of the database makes it highly appropriate for my analysis. Unlike Korean chaebols, there is no formal determination of Indian business groups. Group structure and ownership stakes of the controlling family across different firms are not required to be disclosed except for publicly traded firms. Therefore, the database

[11]Several papers use dispersion in capital productivity as an indicator of capital misallocation. Empirically, Hsieh and Klenow (2009), Bartelsman, Haltiwanger, and Scarpetta (2013), Midrigan and Xu (2009) use dispersion as a country-level indicator of misallocation and find it takes larger values for developing than developed countries. Over business cycles, Eisfeldt and Rampini (2006), Chen and Song (2013), Gilchrist, Sim, and Zakrajek (2012) note that dispersion in capital productivity increases during recessions.

creates these firm-group matches by collecting information from firm annual reports and by continuously monitoring the announcements made by firms. This firm-group matching scheme is quite robust and has been previously used in Khanna and Palepu (2000), Gopalan, Nanda, and Seru (2007) and Alfaro and Chari (2014).

I restrict my sample to stand-alone and business-group firms that operate within the manufacturing sector between 1995-2013. In every year of this sample period, I drop firm-years that belong to business groups of (firm) size less than two. The variables that I use are firm value added, wage bill, capital stock, along with their age and the 2-digit industry that firms belong to. Capital stock is measured empirically using a firm's reported gross fixed assets and computed using the Perpetual Inventory method. Investment is defined as the growth rate of capital stock while accounting for asset depreciation.[12]

The methodology sketched in Section 2.1 uses different moments of the capital profitability ratio to identify parameters of the investment distortions distribution. For the structural estimation procedure, I specify capital and labor intensities at the 2-digit Indian industry level and these are equal to $\alpha_{ks} = \mu(1 - \beta_s)$, $\alpha_{ls} = \mu\beta_s$. Here, μ denotes the markup which is assumed to be constant across all firms and across all industries. β_s is the labor share value for industry s and like Hsieh and Klenow (2009), I assume that these values are equal to the values for the corresponding 2 digit industry in the US. This assumption implies that firms in US and Indian manufacturing industries employ the same production technology and any observed variation in capital and labor revenue productivity ratios is solely due to differences in firm-level distortions. As they argue, in the absence of this assumption, it is not possible to separately identify the average factor elasticity for the Indian industry from the average factor distortions that firms in that industry face.

I match Indian and US manufacturing industries at the 2-digit level and use data reported by the US Bureau of Economic Analysis to compute labor share β_s using the variables Gross Value Added GVA_s and Labor Compensation $COMP_s$.
Capital profitability is empirically defined as the profit generated by the firm (net of labor and material costs) per unit capital owned by the firm,[13]

$$\frac{R_{it}}{K_{it}} = \frac{ValueAdded_{it} - Wage_{it}}{Capital_{it}} \tag{1.31}$$

To ensure that the identification results are robust and not driven by extreme observations, firm-years are dropped that have productivity values in the top and bottom 5 percentiles. All the above variables have been deflated into real values - firm (final good) industry deflators are used to deflate value added, wage bill variables, whereas the capital goods deflator is used to deflate capital stock and investment variables.

These restrictions give me an unbalanced panel of approximately 20,000 business-group firm-years and 42,000 stand-alone firm-years. The proportion of private firms within this sample is quite high - they comprise 54 percent in the entire sample, 39 percent amongst business-group

[12]The flow variables - capital expenditures and asset sales are available for very few firms due to limited reporting of firm cash flow statements.

[13]Although most of the earlier literature uses moments of the capital revenue productivity ratio, my analysis uses capital profitability ratio as I focus on investment distortions only. In the data I find that a strong positive correlation exists between these two time series.

firms and a larger 61 percent amongst stand-alone firms.

Summary statistics

In Table 1.1, I present summary statistics (mean and dispersion measures) for various production variables across stand-alone and business-group firms in India. The table shows a visible age and size difference between stand-alone and business-group firms. Business-group firms tend to be older; the average business group firm is 29 years whereas the average stand-alone firm is 21 years. With respect to firm size, irrespective of the production variable used, firm value added, capital stock or wage bill, business-group firms tend to be larger than stand-alone firms. When I perform a t-test of the means, I find these age and size differences to be statistically significant at the 1 percent level.

There also appears to be greater heterogeneity in firm size amongst business-group firms than stand-alone firms. The dispersion and interquartile range is 1.69 and 2.29 for business-group firms whereas, these values for stand-alone firms are lower at 1.52 and 2.03 respectively. Hsieh and Klenow (2009) characterize the efficient firm size distribution as one which is more dispersed, has fewer medium-sized firms and fatter tails i.e. a larger number of small and large-sized firms. If firm-level policy constraints manifest themselves as a less dispersed firm size distribution then, then the lower firm size dispersion for stand-alone firms also provides evidence for higher firm-level frictions.

The mean growth rate of assets and labor are similar for both types of firms. Relative to labor, firms tend to use more capital in their production processes. This is especially true for stand-alone firms. Their mean and dispersion in capital-to-labor ratio is higher than that for business-group firms. This higher capital intensity could be a result of the restrictive labor laws that Indian manufacturing sector firms need to follow. By operating on the capital-labor margin, these laws can increase the relative price of labor and thus, lead firms to switch to more capital intensive modes of production.[14]

Distribution of organizational structure by Firm size

In Figure 1.1, I give some stylized facts on the distribution of stand-alone and business-group firms within different size quintiles in India. These statistics are computed as the proportion of stand-alone and business-group firms in every size quintile for each year and for each two-digit industry, which are then averaged over the entire sample. As can be seen from the table, there exist significant size differences between these two firm types. In the bottom two size quintiles, there is a higher concentration of stand-alone firms. The proportion of stand-alone firms in Size quintiles 1 and 2 are about 85 percent. As firms become larger, the composition of these size quintiles changes i.e. the concentration of stand-alone firms monotonically decreases. In the largest size quintile, we see that the proportion of stand-alone firms dramatically decreases to 36 percent.

[14] Labor market regulations in India are especially stringent. According to the World Bank's Doing Business report, surveyed firms in India ranked labor market frictions as one of the biggest impediments to firm growth and development. There is also considerable variation in these laws across Indian states. Besley and Burgess (2004) provide detailed information on these laws and the various amendments that Indian states made to their Industrial Disputes Act, 1997.

Table 1.1: Statistics on firm age and firm production variables in the Indian manufacturing sector over the period 1995-2013

	Mean		Dispersion		Inter-quartile range	
	Stand-alone	Bus. group	Stand-alone	Bus. group	Stand-alone	Bus. group
Age	21.48	29.35	16.09	21.34	15	26
Production variables						
log(Value added)	18.4	20.0	1.52	1.69	2.03	2.29
log(Capital)	18.77	20.27	1.35	1.64	1.75	2.27
log(Wage bill)	16.32	17.97	1.52	1.62	2.08	2.19
Investment	0.14	0.14	0.28	0.25	0.15	0.15
Wage growth	0.13	0.12	0.25	0.20	0.23	0.18
Capital/Labor	18.37	16.08	22.31	20.02	16.30	14.12

Data are from the Prowess database. Age of a firm is computed from its year of incorporation. Value added is the sales generated from a firm's business activities net of its expenditures on raw materials. Capital stock is constructed using the Perpetual Inventory method using firm's gross fixed assets. Wage bill is the total salaries and benefits paid to employees. The unit of value added, capital stock and wage bill is constant rupees million.

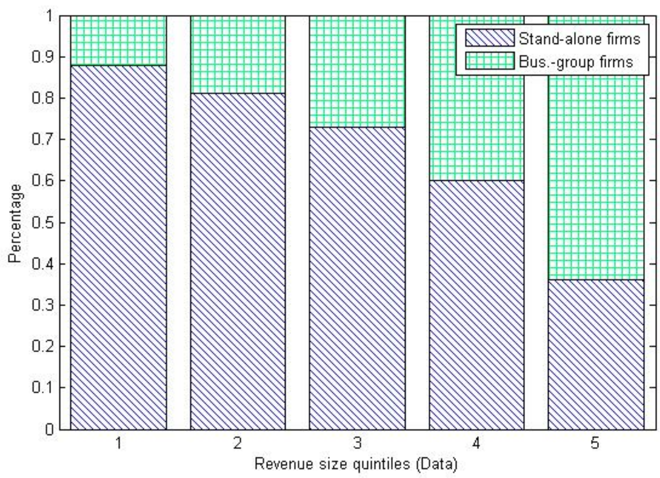


Figure 1.1: Distribution of organizational structure by Firm size

1.2.3 Structural identification of investment distortions and firm organizational structure

To identify firm-level investment distortions and separate their distortionary effect from the effect of unobserved firm-level productivity shocks, I propose a structural estimation procedure that can be used to recover the underlying parameters. In this section, I first explain what moments I use to identify the parameters and then describe the results that I obtain from applying the estimation procedure to Indian firm-level data.

Exogenous parameters

I solve the model described in Section 2.1 using the principles of dynamic programming. After solving for the firm's investment policy function, I simulate a panel dataset which consists of 10000 firms that operate for 200 years and calculate target moments from the last 18 years of this panel. I exogenously assign values to the interest rate, economic depreciation rate and firm-level markup based on earlier studies. The corporate real interest rate r for firms in India is set equal to 0.10 and is consistent with World Bank estimates. Capital depreciates at a rate $\delta = 0.10$ and the value of firm/industrial level markup μ is exogenously set to 0.81 as used by Bachmann, Caballero, and Engel (2013). The price of capital goods P_k is normalized to 1.

Matching Moments

The rest of the parameters namely the persistence, volatility of the productivity shocks and the volatility of investment distortions, $\phi = (\rho^t_{Zs}, \sigma^t_{Zs}, \sigma^t_{Ks})$, I estimate using the simulated method of moments. I first estimate these parameters for the entire sample of stand-alone firms and entire sample of business-group firms. I then estimate these parameters at 2-digit industry levels and across different firm size quintiles to ensure that prior findings obtained about stand-alone and business-group firms are robust.

Now I compute four moments from the data and the model and match the corresponding values to identify the above unknown parameters. Firstly, the persistence of productivity shocks ρ^t_{Zs} is identified from the serial correlation of firm revenue. Across all industries, the serial correlation of firm revenue is 0.95 for stand-alone firms and slightly higher at 0.97 for business-group firms. From identification equation 1.27, we find that both volatility in productivity shocks and volatility in investment distortions positively affect the sample mean and sample dispersion in (log) capital productivity ratios. Therefore, I include these moments as target moments to identify σ^t_{Zs} and σ^t_{Ks}. As explained before, when capital is a dynamic input, volatile productivity shocks can also generate higher sample dispersion in capital profitability. Firm's capital stock is chosen one period in advance and depending on the realization of the productivity shock, it can either be smaller or larger than the new static optimal target of the firm. Investment distortions generate dispersion in capital productivity as they directly affect the marginal revenue product of capital for the firm for each period. To separately identify σ^t_{Zs} I also include the mean and standard deviation of firm's investment rate distribution. I include these moments because firm-level investment rates are unaffected by the level of investment distortions that firms draw at the beginning of their lifecycle. (This can be easily shown analytically using the model.) This implies that moments of the investment rate are used to

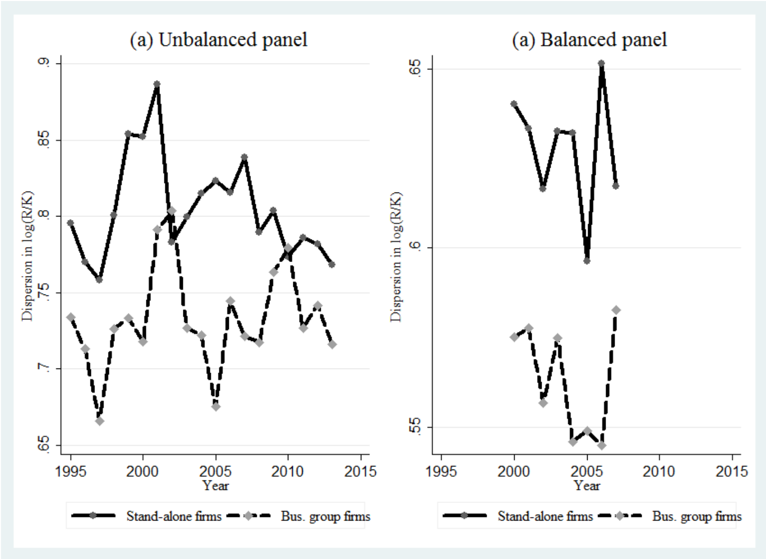


Figure 1.2: Dynamics of within-industry dispersion in log capital productivity in the Indian manufacturing sector, 1995-2013

independently identify how volatile firm productivity shocks are and segregate the effects of productivity shocks and investment distortions.

Dynamics of dispersion in (log) capital profitability

Before presenting the results from the structural estimation, in Figure 1.2, I first plot the dispersion in (log) capital productivity ratio over the entire sample period. (This moment is a target moment in the above structural estimation procedure.) I plot these dynamics for an unbalanced firm sample and a balanced firm sample. Dispersion is computed within every industry for each sample year and organizational firm type and then aggregated across all industries. Firstly, we can see that there is significant dispersion in capital productivity. Dispersion is approximately 0.77 when all firm-years are pooled. If high dispersion is symbolic of the higher capital market imperfections in India, then the above graph suggests that post 1995 (post liberalization), imperfections have not improved. This observation is consistent with Bollard, Klenow, and Sharma (2013) who decompose Indian manufacturing growth using plant-level data and find that much of the growth is due to growth within-plants instead of reallocation of factors between-plants.

If we split firms according to their organizational form then, we can see that stand-alone firms display larger dispersion values. While the dispersion is 0.73 for business-group firm years, it is higher at 0.79 for stand-alone firms. This relation is stable over time and is not affected if we use an unbalanced firm panel or a balanced firm panel. Infact using the balanced firm sample, we can see that gap between the dispersion for stand-alone firms and business-group firms increases over much of the period 2000-2005. Over this period, dispersion for stand-alone firms increases more than the dispersion for business-group firms.

Mean investment distortions across firm organizational structure and within industries

In Table 1.2, I report the results from the structural estimation procedure that I carry out for stand-alone and business-group firms. I first estimate the parameters for the entire universe of industries and then for each two-digit manufacturing industry level. To ensure that product-market competition is not driving the results, I also compute the Herfindahl Index for different industries and analyze whether the estimated distortions vary in any significant way across competitive, less competitive and concentrated industry sectors.

Firstly, I find that most Indian industries are competitive. About 13 industries have Herfindahl index values of less than 0.10. These industries comprise most of the manufacturing sector. Out of the remaining industries, 5 are slightly less competitive and these consist of wood, leather and auto industries and 4 are very concentrated with large Herfindahl index values that are greater than 0.50.

I then investigate whether the estimated standard deviation of productivity shocks varies across two-digit industries. I find that there is not much variation in this measure across industries and across stand-alone firms and business-group firms. Most of the estimated values lie within the $[0.03 - 0.04]$ range. For stand-alone firms, their volatility is lowest (0.016) in the concentrated tobacco sector and highest (0.05) in the motor vehicles and transport equipment sector. Note that this volatility is estimated by using the mean and standard deviation of firm investment rates as moments to match.

Peters (2011) suggests that higher markups could be responsible for the larger distortions for large sized firms (as opposed to market frictions). If larger firms control larger market shares in their industry then, their profit maximizing objective results in them producing too little output, using too little capital and labor. , I assume that firm markups are the same across large and small firms. However, if there are unobserved heterogeneities in firm markups which are increasing with firm size then, this would also imply larger mean investment distortions for larger firms.

Mean investment distortions across firm organizational structure and firm size

Table 1.3 reports the mean investment distortions across different firm classifications: (a) across stand-alone and business-group firms and (b) across different firm sizes.

Firstly, we observe that the levels of distortions are very high. The above model says that in a frictionless world, mean distortions would be equal to 1 across all types of firms. This is clearly not observed in the data suggesting that frictions could be responsible in generating such large deviations in capital stock from the optimal levels. Secondly, if we look across firm size, we find that mean investment distortions are increasing with firm size. Distortions for firms in size quintile 4 are almost 60 percent higher than mean distortions for firms in size quintile 2. This is consistent with the findings of Hsieh and Klenow (2009) and Hsieh and Olken (2014), who report an increasing relation between firm total factor revenue productivity and firm size in India and China but not for the US. Based on these observations, they contend that these higher revenue productivity measures are reflective of the higher (regulatory, institutional) constraints that Larger not smaller firms face in developing countries.

Table 1.2: Estimated values of mean investment distortions and volatility of productivity shocks for firms belonging to the Indian manufacturing sector over the sample period 1995-2013

	No. of firm-years		$\mathbb{E}(1+\tau^t_{Ks})$		σ^t_{Zs}	
	Stand-alone	Bus. group	Stand-alone	Bus. group	Stand-alone	Bus. group
All industries	41664	19924	1.48	1.39	0.036	0.032
Competitive industries - Herfindahl Index <= 0.10						
Food and beverage	4736	2094	1.57	1.54	0.032	0.031
Textiles and apparel	6078	2388	1.47	1.49	0.037	0.034
Pulp and Paper	2012	441	1.29	1.32	0.035	0.034
Chemical and pharmaceutical	8550	4012	1.51	1.43	0.037	0.034
Rubber, plastic and non-metallic mineral	4842	2469	1.43	1.30	0.034	0.032
Metal and metal products	6014	2515	1.42	1.45	0.036	0.038
Computer, electronic and electrical	3233	1758	1.59	1.49	0.036	0.031
Machinery and equipment	1891	1044	1.48	1.40	0.036	0.032
Less competitive industries - Herfindahl Index $\in [0.10 - 0.30)$						
Wood and leather products	829	222	1.55	1.42	0.032	0.030
Motor vehicles and transport equipment	2161	1548	1.24	1.22	0.051	0.035
Other Manufacturing	746	95	1.63	1.78	0.034	0.025
Concentrated industries - Herfindahl Index >= 0.50						
Coke and refined products	329	108	1.77	1.54	0.031	0.033
Tobacco	42	30	1.58	1.2	0.016	0.035
Printing and publishing	188	40	1.44	1.51	0.030	0.033
Furniture	62	39	1.57	1.25	0.037	0.022

Firm industries are defined at the two-digit manufacturing industry level and over the sample period 1995-2013. The Herfindahl-Hirschman Index is used to group industries into competitive sectors, less competitive sectors and highly concentrated manufacturing production sectors. The estimation procedure is carried out independently for the sample of stand-alone and business-group firms at (a)the aggregate industry level (i.e. by grouping all industries together) and at (b)individual two-digit industries. In the table, I present the estimated values for mean investment distortions and volatility of firm-level productivity shocks.

Table 1.3: Mean investment distortions across Firm sizes and across stand-alone and business-group firms in the Indian manufacturing sector, 1995-2013

	$\mathbb{E}(1+\tau_k)$ Stand-alone (1)	$\mathbb{E}(1+\tau_k)$ Bus.-group (2)	$\mathbb{E}(1+\tau_k)$ difference (1)/(2)
All Sizes	1.82	1.78	1.02*
Size quintile 1	1.01	1.15	0.88
Size quintile 2	1.49	1.32	1.14*
Size quintile 3	1.87	1.84	1.02*
Size quintile 4	2.40	2.19	1.10*
Size quintile 5	2.42	2.33	1.04*
No. of firm-years	19994	41593	

Revenue size quintiles are defined over the entire sample of manufacturing sector firms. The first moment of investment distortions have been computed within each combination of 2-digit industry and organizational structure of the firm. Industry-specific labor shares are used to compute these moments.

I now look at how mean investment distortions vary across stand-alone and business-group firms. If all firm-years are pooled together then, mean investment distortions are 2 percent higher for stand-alone firms than business-group firms. If I segregate firms according to their firm size, then again I observe that except for the smallest size quintile, mean investment distortions are higher for stand-alone firms. While in the smallest size quintile, mean investment distortions are about 10 percent higher for business-group firms than stand-alone firms. In the larger size quintiles, however, this finding gets reversed. Large stand-alone firms face larger distortions that varies from a minimum of 2 percent and a maximum of 10-14 percent in Size quintile 2 and 5 respectively. This finding is surprising as investment distortions are not consistently larger for Business-group firms but, firm size also seems to play a role in determining firm-specific distortions. Note that frictions could be the most plausible explanation for higher mean investment distortions for stand-alone firms as it is less likely that large stand-alone firms impose higher markups than large business-group firms.

Therefore, the findings of this section can be summarized as,

1. Amongst larger firms, mean investment distortions are larger for stand-alone firms. Amongst the smallest firms however, this finding gets reversed. Distortions are larger for business-group firms.

2. Within-industry dispersion in capital revenue productivity ratio is consistently larger for stand-alone firms over all sample years.

3. Mean investment distortions increase with firm size (revenue)

4. Stand-alone firms are more likely to be concentrated in the smaller size quintiles whereas business-group firms are more likely to be concentrated in the larger size quintiles

In the next section I develop a dual-industry model of firm dynamics which is consistent with these empirical findings. The main features of the model economy are: firm organizational (diversification) decision is endogenous. Firms face two types of capital market imperfections in the economy: investment is irreversible and financing frictions increase the reduced-form costs of external finance for firms.

1.3 Endogenous investment distortions and firm organizational structure

I now introduce a dual-industry model which consists of heterogeneous firms. The model is set in partial equilibrium. In Section 5, I estimate this model so that it can explain the empirical findings described in the previous section.

I motivate the main features of this model. In each industry, firms operate a decreasing returns to scale production technology that uses a dynamic input capital and a static input labor. Firms in this economy can either be stand-alone firms or business-groups. Stand-alone firms produce only a single industry's good. Business groups are diversified entities that consists of two firms and produce goods of both industries. Firms in every period choose their organizational structure. After choosing their organizational structure, they decide how to allocate their factors between the two industries. Stand-alone firms allocate all their factors to a single industry, whereas business-group reallocate resources across both firms (both industries).

Firms then decide how much to invest. I assume that investment decisions are irreversible. This assumption is consistent with the investment rate distribution observed for Indian firms. Capital sales are infrequent, mean disinvestment rate is only 2 percent and firms display large periods of inaction. Financial frictions also exist within this economy. If firm's internal funds are insufficient to finance factor payments then, they can issue external finance which are associated with proportional costs as assumed by Gomes (2001), Hennessy and Whited (2007).

Firm diversification in this model is optimal and arises due to the same economic reasons as studied by Maksimovic and Phillips (2002) and Gomes and Livdan (2004). Decreasing returns to scale ensures that firm growth in any industry is bounded. Therefore, firms grow across industries to capture new growth opportunities. While these papers use the model to explain the diversification discount empirically observed for US conglomerates, I use it to study why and how capital misallocation varies between stand-alone and business-group firms.

I also build on this class of models by introducing capital adjustment costs and financing frictions faced by firms. In single industry models, we know that adjustment and financing frictions generate investment distortions (Asker, Collard-Wexler, and De Loecker (2014), Midrigan and Xu (2009), Midrigan and Xu (2014)). I show that when firm organizational structure is endogenously determined, these frictions have differential effects on the investment and financing decisions of stand-alone firms and business-group firms.[15]

I consider a discrete time, infinitely-lived partial equilibrium economy which consists of two industries - 1 and 2. The total measure of firms within economy is N and each firm has some market power in producing its differentiated good(s).

1.3.1 Organizational form

There are two types of firms in the economy - stand-alone firms and business-groups. While stand-alone firms only produce goods in one industry, business-groups are diversified and produce goods in both industries.[16]

Each period corresponds to one year. Firm i enters the period as a stand-alone firm or a business group and its accumulated capital stock and liquid assets are denoted by K_i and B_i respectively. Stand-alone firms produce output goods of only one industry (either industry 1 or 2) and equivalently their sector state variable $s_{i,-1} = 1$ or 2. Alternatively, if the firm is a business group, then it produces goods of both industries and its state is denoted by $s_{i,-1} = 3$.

Firm i observes its idiosyncratic productivity shocks for both industries, $Z_i = (Z_{1i}, Z_{2i})$ and then decides whether it wants to remain in its initial industry (state) or change its industrial state.

The shocks that firm i draws for both the industries are assumed to be uncorrelated to each other and follow an AR(1) process. Additionally, I assume that both productivity shocks are drawn from a common distribution with persistence ρ_z and long-run uncertainty σ_z. Therefore, I abstain from introducing any heterogeneity at the industrial level.

$$ln(Z_{ji}) = \rho_z ln(Z_{ji,-1}) + \sigma_z \epsilon_{ji} \quad j = \{1, 2\} \tag{1.32}$$

[15] In the model specification assumed here, firms cannot accumulate any liquid assets apart from risky productive capital and they face costly external financing. Therefore, the precautionary motive would result in them over-accumulating capital. Increasing the space of assets that firms can invest in would bring the model closer to reality, but would not change the results significantly. I am currently working on an alternative version of the model which allows firms to invest in productive capital and liquid assets. However, the increasing dimensionality makes the computation procedure non-trivial. Due to investment irreversibility, the investment policy function is non-linear and requires a dense grid. If a sparse grid is used, the accuracy of the model and the results decrease significantly.

[16] Since, most business-groups in India and in several other countries feature high levels of horizontal diversification, this assumption seems appropriate. In the model, firms cannot diversify across more than two industries whereas in reality, most business groups/conglomerates operate over multiple industries. While extension of the model to more than two industries would capture this fact better, it would also make the computational problem more complex to solve. Also, as the model does not include any strategic reasons due to which firms diversify, inclusion of multiple industries would not change the underlying reasons why firms diversify and only make the results stronger.

Both ϵ_{1i} and ϵ_{2i} are assumed to be i.i.d. processes.

A firm that was stand-alone in the previous period, can either continue to remain in its own industry $s_{i,-1}$ or it can diversify to both industries. A firm that was a business group in the previous period has more sectoral choices. It can stay diversified or it can become a stand-alone firm in any one of these two industries. The industrial choices are depicted by,

$$s_i = \begin{cases} \{s_{i,-1}, 3\} & s_{i,-1} = 1, 2 \\ \{1, 2, 3\} & s_{i,-1} = 3 \end{cases} \tag{1.33}$$

These choices imply that a stand-alone firm in industry i cannot directly switch its productive activities to industry j but, has to diversify in the intermediate stage.

1.3.2 Production

Production in each industry occurs according to a decreasing returns to scale function that uses capital and labor. Labor is a static input for the firm that is inelastically supplied in the economy at an exogenous wage cost W whereas capital stock K_i is accumulated by firms.

In addition to paying wages, firms also pay fixed operating costs which, are assumed to be higher for business-group firms. As Gomes and Livdan (2004) show, these additional fixed costs for business-groups ensure that the stationary distribution of firms consists of a non-zero measure of stand-alone firms. If fixed costs were identical for both stand-alone and business-groups then all firms will choose diversification as their optimal policy.

If firm i is a stand-alone firm then it allocates all its inputs to the single industry and generates profits net of operating costs given by,

$$F(s_i, Z_i, K_i) = max_{L_{si}} \left[Z_{si} K_i^{\alpha_k} L_{si}^{\alpha_l} - W L_{si} - f \right], \quad s_i = 1, 2 \tag{1.34}$$

If firm i is a business group, then I assume that factor allocation decisions are made at the headquarter level. Group headquarters observe their productivity shocks for both industries and optimally decide in what proportion capital and labor are distributed across the two industries. Let θ_i denote the amount of capital/labor that is allocated to Industry 1 segment. Then the total profits for the group are given by,

$$F(3, Z_i, K_i) = max_{\theta_i, L_i} \Big[Z_{1i} (\theta_i K_i)^{\alpha_k} (\theta_i L_i)^{\alpha_l} \tag{1.35}$$

$$+ Z_{2i} ((1-\theta_i) K_i)^{\alpha_k} ((1-\theta_i) L_i)^{\alpha_l} - W L_i - 2f \Big]$$

Solving for θ_i, the above can be written as,

$$F(3, Z_i, K_i) = max_{L_i} \left[\left(Z_{1i}^{\psi} + Z_{2i}^{\psi} \right)^{\frac{1}{\psi}} K_i^{\alpha_k} L_i^{\alpha_l} - W L_i - 2f \right] \tag{1.36}$$

where $\psi = \frac{1}{1 - \alpha_k - \alpha_l}$.

Here, $F(s_i, Z_i, K_i)$ denotes the per-period profit function for firm i obtained after maximizing out labor from the above problem.

1.3.3 Investment and adjustment costs

Conditional on the industrial choice s_i made by firm i, it also decides to accumulate capital by investing I_{si}. The law of motion for firm's capital accumulation is given by,

$$K'_{si} = K_i + (1 - \delta)I_{si} \tag{1.37}$$

Firm investment is irreversible and is subject to quadratic adjustment costs. The functional form of the adjustment cost function is given as,

$$C(I_{si}, K_i) = I_{si}\mathbb{I}_{I_{si}>0} + \frac{c_q}{2}\left(\frac{I_{si}}{K_i}\right)^2 K_i \tag{1.38}$$

I assume this specification for adjustment costs as Indian manufacturing firms display significant inertia and asymmetry with respect to their investment choices. Only 6 percent of the total sample of firms disinvest and their average disinvestment rate is small at 2 percent. It also must be noted that the empirical investment rate is smooth, the autocorrelation is 0.30 suggesting existence of quadratic costs being incurred at the firm-level. The smoothing cost parameter c_q is homogeneous across firms and its value will be estimated in the next section.

1.3.4 Financing

The budget constraint for firm i is given by equating firm's internal source of funds (firm revenue) to its use of funds (wage payments, fixed costs, capital investment and adjustment costs and payouts to firm claimants),

$$d_{si} = F(s_i, Z_i, K_i) - C(I_{si}, K_i) \tag{1.39}$$

Financial market imperfections exist within this economy that can arise due to several reasons: adverse selection, poor contract enforcement, inefficient bankruptcy laws, imperfect competition in the financial sector. Following the approach of Gomes (2001), Hennessy and Whited (2007), I do not explicitly model the underlying friction but parameterize a reduced form for it. I assume that if firms generate insufficient internal funds they can issue external finance which is costly and associated with proportional costs.

Therefore, the per-period payoff for firm i's shareholders is the dividend payout if there is no requirement for external finance. Else, if the payout is negative, costly external finance is issued by firms,

$$d_{si} + \phi(d_{si}) = \begin{cases} d_{si} & : d_{si} \geq 0 \\ d_{si} + \phi_1 d_{si} & : d_{si} < 0 \end{cases} \tag{1.40}$$

The parameter ϕ_1 is estimated in the next section and will give us some evidence on how costly is external financing for firms in India.

1.3.5 Firm's Problem

The dynamic Programming problem for firm i is split in two stages.

- In the first stage, the firm observes its productivity shocks for the current period and chooses its optimal organizational form i.e. its industrial state for the current period s_i. A stand-alone firm can produce goods of a single industry or it can diversify into both industries, whereas a business group can remain diversified or operate in only one of the two industries. The value function associated with this stage of the firm is given by,

$$V(s_{i,-1}, Z_i, K_i) = max_{s_i=\{s_{i,-1},3\}} \{P(s_i, Z_i, K_i)\} \tag{1.41}$$

  and

$$V(3, Z_i, K_i) = max_{s_i=\{1,2,3\}} \{P(s_i, Z_i, K_i)\} \tag{1.42}$$

  respectively.

- After choosing its optimal organizational form, the firm invests in productive capital and can issue costly external finance,

$$P(s_i, Z_i, K_i) = max_{I_{si}} \left\{ d_{si} + \phi(d_{si}) + \frac{1}{1+r} \int V(s_i, Z_i, K'_{si}) Q(Z_i|dZ'_i) \right\} \tag{1.43}$$

  s. to

$$d_{si} = F(s_i, Z_i, K_i) - C(I_{si}, K_i) \tag{1.44}$$

$$K'_{si} = I_{si} + (1-\delta)K_i \tag{1.45}$$

  and,

$$I_{si} >= 0 \tag{1.46}$$

1.4 Model Decision Rules

In this section, I present the decision rules of firms that are obtained after numerically solving and calibrating the above model.

1.4.1 Numerical procedure for solving model

Since, analytical solutions of the model cannot be obtained, I numerically solve the model using Value Function Iteration. I discretize the state space for (s, Z_1, Z_2, K). The organizational state of the firm can take three values $s = \{1, 2, 3\}$. The state $s = 1, 2$ refers to stand-alone firms in industries 1 and 2 whereas, the state $s = 3$ refers to the firm as a business group. Productivity shocks for both industries follow an AR(1) process which is transformed into a discrete-state Markov Chain using the method in Tauchen (1986). Each productivity shock can take 15 values

Table 1.4: Exogenous parameter values

Real interest rate	r	0.10
Economic depreciation rate	δ	0.10
Markup in product market	μ	0.81
Labor share	β	0.56
Per unit cost of labor	W	0.5

These parameters are exogenously assigned values and are used in the model calibration and estimation exercises.

and belongs to a bounded set $[-3\sigma_z/\sqrt{1-\rho_z^2}, 3\sigma_z/\sqrt{1-\rho_z^2}]$. Current and future capital stock K and K' lie on grids with 330 points. The model results do not change significantly if more grid points are included in this set. In model simulations, I ensure that the upper bound of these grids is never reached.

I first solve the model computationally to obtain firm's Value function and the decision rules for diversification and capital accumulation. I then simulate an artificial economy that consists of 10000 firms for a period of 200 years. I only keep the last 18 years of this simulated sample so that its length is identical to the length of the Indian panel data sample.

Exogenous parameters

In Table 1.4, I display the set of parameters that are estimated out of the model and are exogenously assigned values based on past literature. The parameters that also appear in Section 2 assume the same values. The real interest rate that firms use to discount future profits is set to 0.10, capital depreciates at a rate of 0.10. The capital and labor share coefficients in firms production function are defined as $\alpha_k = (1-\beta)\mu$ and $\alpha_l = \beta\mu$. Here, μ is the parameter associated with firm's markup and is assumed to be 0.81 implying a 23 percent markup for Indian firms. β is the labor share which is the average labor share computed, by pooling all 2-digit Indian industries. As discussed in Section 2, by making the assumption that Indian and US industries share the same technology parameters, I can use data on labor share for matched US industries. This exercise gives me an average labor share value of 0.54. I follow Gomes and Livdan (2004) and assign a value of 0.5 to the per-unit cost of labor, W.

In the next section, I estimate the remaining parameters of the model. These parameters are: fixed operating costs of firms f, persistence ρ_z and standard deviation σ_z of industrial productivity shocks, the quadratic adjustment cost parameter c_q and the external financing cost parameter ϕ_1. I denote this parameter vector by $\theta = \{f, \rho_z, \sigma_z, c_q, \phi_1\}$.

I now provide information on the various policy rules of firms. For these policy rules, I assign exogenous values to θ. Fixed costs equal to 0.35 imply a 60 percent of business-group firms in the simulated sample. I assume productivity shocks are quite persistent, ρ_z takes a value of 0.90 and uncertainty of productivity shocks is low at 0.05. I also assume modest values for the adjustment cost and financing cost parameters, $c_q = 0.05$ and $\phi_1 = 0.05$. I first use the model to explain the region in the productivity shock-capital state space where firms choose to diversify. I then explain how irreversibility, financing costs endogenously generate higher investment wedges for stand-alone firms. I map the endogenously generated wedges to firm's investment Euler equation to build this argument. I finally perform comparative static exercises and display results on the investment wedges across stand-alone and business-group firms using the simulated model. This exercise enables me to fit the empirically identified investment distortions pattern and hence, estimate the unknown model parameters.

1.4.2 Diversification Decision

A Firm's decision to diversify or focus its operations depends on its growth opportunities in each industry. These growth opportunities in turn depend on its industry-specific productivity shocks (Z_{1i}, Z_{2i}) and its accumulated capital K_i.

In Figure 1.3, I plot the region over which firms choose to diversify. The top three plots represent the decision rules for a stand-alone firm in Industry 1 and the bottom three plots represent the decision rules for a business group.[17] The checked area is where a Business group is formed. The dashed and plain areas are where firms choose to focus and form stand-alone firms in industries 1 and 2 respectively.

A stand-alone firm will remain undiversified when its own productivity Z_{1i} is relatively higher than Z_{2i}, i.e. industrial productivity shocks are asymmetric. This is seen in the dashed regions in the top left and middle plots. In this scenario, group formation is associated with low overall value as resources have to be split between the high and the low productivity industry and higher fixed costs need to be paid for the firm. A stand-alone firm will however, diversify if it receives low productivity shocks in both industries (Z_{1i} and Z_{2i} are low) or if its growth opportunities in the other industry are high, Z_{2i} is high. This is represented by the checked area in all three plots. Here, a firm's capital stock K_i also affects diversification decisions. Given any set of productivity shocks, as K_i increases, firm's marginal productivity of capital falls in its own industry due to the assumption of a decreasing returns to scale firm production function. Hence, firms optimally diversify in search of more growth opportunities. Gomes and Livdan (2004) use this prediction of the model, the endogenous selection of firms into diversification to explain the diversification discount for conglomerates in the US.

In the bottom three plots, diversification decisions are traced for business groups. Comparing the top and bottom plots, we find that the diversification decision is similar for stand-alone firms and business groups. Business groups focus when they receive asymmetric productivity shocks and they remain diversified when the industrial productivity shocks are similar. However, in contrast to stand-alone firms they can directly switch to industry 2 when Z_{1i} is low and Z_{2i} is medium or high. This is depicted using the plain area in the bottom middle and bottom right plots.

[17] The same argument will hold if we were to look at a stand-alone firm in Industry 2.

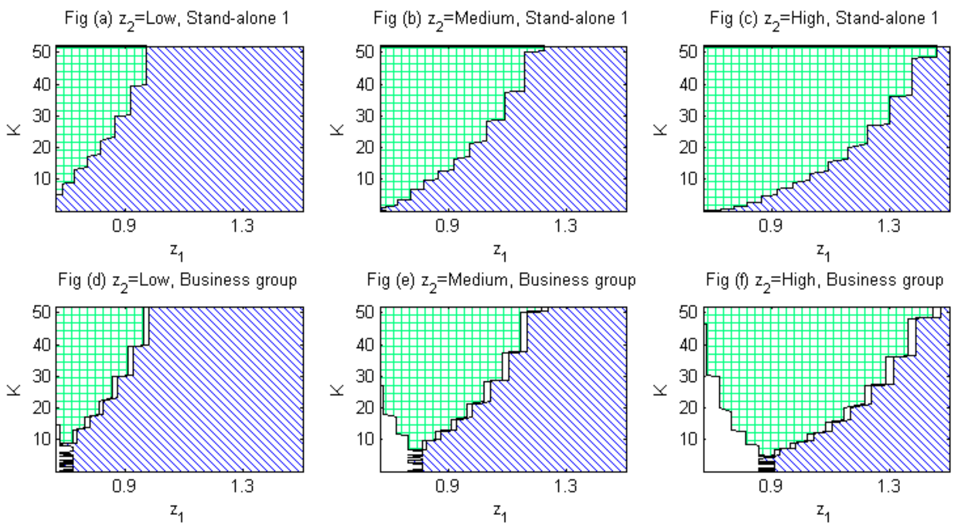


Figure 1.3: Optimal diversification regions for stand-alone firms and business groups (dashed region - firms produce in industry 1, plain region - firms produce in industry 2, checked region - firms diversify)

1.4.3 Comparative Statics - Capital misallocation

I now perform some comparative static exercises and show whether and to what extent the simulated model can generate investment distortions across different firm sizes and organizational structures. I first analyze the effect of productivity uncertainty on the mean investment distortions and dispersion in log-capital revenue productivity. This is displayed in Table 1.5. We see that when uncertainty is low at 0.05, few large stand-alone firms infact, only the largest stand-alone firms, have higher mean investment distortions than similarly-sized business group firms. For all other size quintiles, distortions are higher for business-group firms. However, the dispersion in capital-revenue productivity ratio is higher for stand-alone firms (0.12) compared to the value for business-group firms (0.09).

I now simulate the model and choose a high value for productivity uncertainty. We see that mean investment distortions sharply increase for large stand-alone firms. The largest stand-alone firms display a value of 1.17 which is almost 15 percent higher than the value observed for business-group firms. The dispersion in capital productivity also increases from 0.12 when uncertainty is low to 0.33 when uncertainty is high for stand-alone firms. The dispersion increases for business-group firms as well however, the increase is much lower as the increase observed for stand-alone firms.

From the above table, we see that productivity uncertainty amplifies the difference in capital misallocation between stand-alone and business-group firms. Capital misallocation and hence, distortions in the model endogenously arise due to investment irreversibility and costly external financing. I now build some intuition on this result by looking at firm's investment Euler equation and examine the effect of each of these market imperfections on both types of firms decisions. The goal of the next two subsections is to show that these imperfections bind more for stand-alone firms than business-group firms.

Table 1.5: Effect of productivity uncertainty - Mean investment distortions by firm size and organizational structure from simulated model

	low $\sigma_z = 0.05$		high $\sigma_z = 0.12$	
	Stand-alone firms	Bus. group firms	Stand-alone firms	Bus. group firms
$\mathbb{E}(1+\tau_k)$				
Size 1	0.90	1.08	0.74	0.84
Size 2	0.93	1.08	0.83	0.83
Size 3	0.95	1.06	0.91	0.85
Size 4	0.97	1.03	1.01	0.89
Size 5	1.03	1.03	1.17	1.01
$\Sigma(log(R/K))$	0.12	0.09	0.33	0.26

Mean investment distortions are computed from the sample of firms simulated from the model for different values of productivity uncertainty. The organizational type of the firm is endogenously determined via the model. The other values of parameters are fixed at: f is 0.35, ρ_z is 0.90, investment adjustment costs c_q and external financing costs ϕ_1 are each equal to 0.05.

1.4.4 Comparitive Statics - Investment policy

In the model, I assume that firm investment is irreversible. This implies that firms cannot reallocate capital in the external market in response to the idiosyncratic productivity shocks they receive each period. In the internal markets of groups however, group headquarters can reallocate capital between firms and industries. In this section, I show that mean investment distortions are larger for large stand-alone firms because they face a higher user cost effect which makes them more reluctant to invest.

To see this, assume that the only friction affecting firm investment decisions is irreversibility. Financing is assumed to be costless, there are no convex adjustment costs and firms receive the entire surplus from production when negotiating with workers. In this situation, the optimal capital stock of firms is of the (s,S) type. We know that when investment is irreversible and uncertainty is high, the dynamics of long run capital accumulation are determined by two opposing forces: the user cost effect and the hangover effect (Pindyck (1988), Dixit (1989), Bertola (1998), Abel and Eberly (1999)).

Following Sim (2007), I represent these two effects using the firm's investment Euler equation. With some abuse of notation, the equation can be written as,

$$1-\lambda_{si} = \frac{1}{1+r}\mathbb{E}_{Z'}\left[\left[R_K(Z'_{1i},K'_{si})+(1-\delta)(1-\lambda_{s'i})\right]\mathbb{I}_{SA'=1}\right] \tag{1.47}$$

$$+\frac{1}{1+r}\mathbb{E}_{Z'}\left[\left[G_K(Z'_{1i},Z'_{2i},K'_{si})+(1-\delta)(1-\lambda_{s'i})\right]\mathbb{I}_{BG'=1}\right]$$

where $R_K(Z'_{1i},K'_{si})$ and $G_K(Z'_{1i},Z'_{2i},K'_{si})$ are the expected marginal revenue products of capital for stand-alone and business-group firms respectively. λ_{si} and $\lambda_{s'i}$ are the current and future

Table 1.6: Proportion of firms with a binding irreversibility constraint

σ_z	0.05	0.06	0.07	0.08	0.09	0.10	0.11
Stand-alone firms	0.33	0.38	0.42	0.45	0.47	0.49	0.50
Bus. group firms	0.21	0.22	0.24	0.26	0.27	0.28	0.29

These statistics are computed from the sample of firms simulated from the model for different values of productivity uncertainty. The organizational type of the firm is endogenously determined via the model. The other values of parameters are fixed at: f is 0.35, ρ_z is 0.90, investment adjustment costs c_q and external financing costs ϕ_1 are each equal to 0.05.

multipliers on the irreversibility constraint for firms. Rearranging this equation I get,

$$1 - \lambda_{si} + \frac{1-\zeta}{1+r}\mathbb{E}_{Z'}\left[\lambda_{s'i}\mathbb{I}_{SA'=1} + \lambda_{s'i}\mathbb{I}_{BG'=1}\right] \tag{1.48}$$

$$= \frac{1-\zeta}{1+r}\mathbb{E}_{Z'}\left[R_K(Z'_{1i}, K'_{si})\mathbb{I}_{SA'=1} + G_K(Z'_{1i}, Z'_{2i}, K'_{si})\mathbb{I}_{BG'=1}\right] + (1-\delta)$$

The left hand side is the marginal cost of investment whereas the right hand side is the expected marginal benefit of investment received by the firm in the next period. The marginal benefit depends on the marginal product of capital and firm's decision of becoming a stand-alone firm or a business group. Also, in contrast to the frictionless case, Lagrange multipliers here endogenously generate investment distortions.

The hangover effect arises when the irreversibility constraint binds for firm i in the current period i.e. $\lambda_{si} > 0$. These firms choose to not invest as the shadow value of capital is low. In Table 1.6, I present the fraction of stand-alone firms and business-groups with a binding irreversibility constraint for several values of uncertainty σ_z ranging from 0.05 to 0.11. Firstly, we see that the proportion of firms with a binding irreversibility constraint increases marginally as uncertainty increases. When σ_z is 0.05, only 33 percent of stand-alone firms and 21 percent of business-group firms would want to disinvest. However, as uncertainty increases to 0.11, almost half of the stand-alone firms and 30 percent of the business-group firms have a binding irreversibility constraint. We also see that at every uncertainty value, stand-alone firms are more likely to have a binding hangover effect (ranges from 33 percent to 50 percent) than business groups (24 percent to 30 percent).[18]

The user cost effect arises when firm i expects the irreversibility constraint to bind in the next period, $\lambda_{s'i} > 0$. A binding constraint increases the marginal cost of investment in the current period (left-hand side of (1.48) increases). For such firms, the disinvestment option is unavailable in future states and this leads to more cautious investment in the current state and a marginal product of capital higher than their frictionless values (positive investment distortion).

However, the user cost effect will bind less for firms that find it optimal to form business

[18]In initial model results, the alternative version of the model with liquid assets also displays this pattern of stand-alone firms facing a more binding irreversibility constraint than business-group firms.

groups in the next period. These firms can reallocate their future excess capital between two industries. Hence, ex-ante they will be less reluctant to invest and their deviations from their frictionless investment choices will be lower. In other words, the higher expected organizational flexibility of business groups translates into a lower current user cost effect.

For a persistent productivity process, stand-alone firms are less likely to diversify and business-groups are more likely to remain diversified in the next period. Therefore, the user cost effect is more likely to bind (positive investment distortions more likely) for stand-alone firms especially if uncertainty, and persistence are high.

1.4.5 Comparative Statics - External financing policy

Costly financing can also increase investment distortions. To see this, assume a version of the model economy in which firm investment is reversible and costly financing is the only capital market imperfection affecting investment decisions. In this scenario, it can be shown that investment distortions are positive for firms that issue external finance or are constrained. To see this, I write down the investment Euler equation in this version of the model,

$$1 + \phi_1 \mu_{si} = \frac{1}{1+r} \mathbb{E}_{Z'} \left[\left[R_K(Z'_{1i}, K'_{si}) + (1-\delta) \right] (1 + \phi_1 \mu'_{s'i}) \mathbb{I}_{SA'=1} \right] \tag{1.49}$$

$$+ \frac{1}{1+r} \mathbb{E}_{Z'} \left[\left[G_K(Z'_{1i}, Z'_{2i}, K'_{si}) + (1-\delta) \right] (1 + \phi_1 \mu'_{s'i}) \mathbb{I}_{BG'=1} \right]$$

where μ_{si} and $\mu'_{s'i}$ are the current and future lagrange multipliers on the external financing constraint. In (1.49), the left hand side is the marginal cost of investment which is higher when firm's external financing constraint binds, $\mu_{si} > 0$. This arises when firm i issues costly finance or is constrained. The right hand side is the expected marginal benefit from current investment for firm i: higher expected revenues and a less binding external financing constraint in the future. Therefore, the optimal investment policy for firm i trades off current and future financing costs. In Table 1.7, for different values of uncertainty, I provide information on the fraction of stand-alone and business-group firms who use external finance and are constrained. We see that business-groups are less likely to use external finance or be constrained. About one-third of stand-alone firms are constrained, while less than 15 percent of business-groups are constrained. Few firms use external finance. While for stand-alone firms, the proportion ranges from 0.11 to 0.15 percent, most business-groups (more than 95 percent) use their internal funds to finance their investment costs. Firstly, the selection effect implies that firms diversify when they are larger. Therefore, the capital stock of the average business group is larger. Also, cash flows are diversified within business groups and these can be used by individual group-firms to fund their investment opportunities. The above implies that the large size and financial pooling ability of business groups reduces their reliance on external funds. In contrast, stand-alone firms are smaller on average, have higher growth opportunities in their industry and their use of external funds is larger. Therefore, the above implies that mean investment distortions will be larger for stand-alone firms than business-group firms.

Table 1.7: Extensive margin of external financing use

Panel A: Proportion of firms using external finance				
σ_z	0.05	0.06	0.07	0.11
Stand-alone firms	0.11	0.14	0.13	0.14
Bus. group firms	0.03	0.04	0.04	0.04

Panel B: Proportion of constrained firms				
σ_z	0.05	0.06	0.07	0.11
Stand-alone firms	0.31	0.30	0.31	0.29
Bus. group firms	0.12	0.11	0.10	0.10

These statistics are computed from the sample of firms simulated from the model for different values of productivity uncertainty. The organizational type of the firm is endogenously determined via the model. The other values of parameters are fixed at: f is 0.35, ρ_z is 0.90, investment adjustment costs c_q and external financing costs ϕ_1 are each equal to 0.05.

1.5 Model Estimation

In this section, I discuss the procedure and the moments used to estimate the unknown parameters of the model. I display the estimated values of these parameters along with their standard errors. I finally perform some out-of-sample predictions from the estimated model to assess the goodness-of-fit of the model.

1.5.1 Estimation procedure

I use an Indirect Inference procedure to estimate the unknown parameters of the model. This method estimates the unknown parameter vector by minimizing the weighted distance between the actual data moments and the model-generated moments. I denote the unknown parameter vector as,

$$\theta = \{f, \rho_z, \sigma_z, c_q, \phi_1\} \tag{1.50}$$

where f are the fixed operating costs that firms pay, ρ_z and σ_z are the persistence and standard-deviation of firm-level productivity shocks, c_q is the quadratic adjustment cost parameter and ϕ_1 are the marginal external financing costs.

To perform the indirect inference procedure, I first choose a set of moments from the data. I denote this vector as M^d. These moments should be informative about the unknown parameters to ensure identification. For an arbitrary value of θ, the same moments are computed from the simulated model which consists of 10000 firms who operate for 200 time periods. The first 182 years are discarded and moments are computed from the last 18 years of the sample. Therefore, the length of the simulated panel is the same length as the actual data panel. I denote this vector of simulated moments as $M(\theta)$.

Then the optimal $\hat{\theta}$ is the parameter vector that minimizes the following criterion function,

$$\hat{\theta} = argmin_{\theta}\mathbb{L}(\theta) = argmin_{\theta}\left[(M(\theta) - M^d)'W(M(\theta) - M^d)\right] \tag{1.51}$$

where W is the weighting matrix. The efficient choice for the weighting matrix is the inverse of the variance-covariance matrix of data moments. W is obtained by bootstrapping repeated samples of the data with replacement.

I also generate standard errors for the parameter point estimates, by computing numerical derivatives of the simulation moments with respect to the parameters and weight them using the optimal weighting matrix. The numerical derivative is defined as $f'(x) = \frac{f(x+\epsilon)-f(x)}{\epsilon}$ and the standard errors are computed as,

$$SE = diag\left[\left[\left[\frac{\partial M(\theta)'}{\partial\theta}W\frac{\partial M(\theta)}{\partial\theta}\right]^{-1}\right]^{1/2}\right] \tag{1.52}$$

where $\frac{\partial M(\theta)}{\partial\theta}$ is the numerical derivative of the simulated model moments and its dimension is ($\sharp$ of moments) $\times$ ($\sharp$ of parameters).

1.5.2 Selection of Moments

I now describe the moments that I use to identify θ. These moments are informative about the parameter vector θ, if they are sensitive to changes in the value of θ. Fixed costs f determine the diversification decision of the firm. If fixed costs are very small, then all firms choose to diversify. If they are very large, then none of the firms choose to diversify. Therefore, the proportion of group firms is informative about f. In Indian firm-level data, business-group firms comprise 35 percent of the total sample of firms, suggesting the existence of high fixed costs that prevent firms from diversifying.

The difference between mean investment distortions for stand-alone and business-group firms is informative about productivity persistence ρ_z, productivity uncertainty σ_z and the external financing cost parameter ϕ_1. To see this, we go back to the discussion of firm investment and financing decision rules that appeared in the previous section. There I explained how investment irreversibility and external financing creates wedges in the Investment Euler equation. Therefore, ρ_z, σ_z and ϕ_1, affect the marginal cost of firm's investment and hence, the mean investment distortions. As ρ_z decreases, σ_z increases, productivity shocks are more uncertain. Therefore, the real options effect causes firms to delay their investment decisions as the disinvestment option is unavailable to them in the future. This effect is especially severe for stand-alone firms who are unable to reallocate their excess capital across multiple industries in the future. As, ϕ_1 increases, the marginal cost (of investment) increases for firms who use external funds to finance their investments. As stand-alone firms are more likely to use external finance in the economy, their mean investment distortions will respond more to increases in ϕ_1.

I include the autocorrelation of firm revenue which is informative about the persistence ρ_z of the industrial productivity shocks. The mean, standard deviation and autocorrelation in firm investment rate are included in the vector of moments as they are sensitive to the adjustment cost parameter c_q. Finally, I include the mean and standard deviation of the external financing rate as additional moments that the model should match. These will also be informative about ϕ_1. Therefore, I use 12 moments to identify 5 parameters implying that the model is overidentified.

1.5.3 Empirical Results

In Table 1.8, I report the actual data moments and the simulated model moments at the estimated parameter values. In the top section of the table, I report the target moments that are used to match in the indirect inference procedure. In the bottom section, I report other moments which are not the statistics of interest and can tell us about the ability of the model to match other dimensions.

The model fits the data quite accurately. The proportion of business-group firms as generated by the model is 0.45, which is slightly higher than what is observed in the data. The autocorrelation of firm revenue, mean and standard deviation of firm investment rates match perfectly. One area where the model does poorly is the autocorrelation of firm investment. The simulated model predicts very smooth investment rates, the magnitude of the autocorrelation of firm investment is 0.50 which is significantly higher than its empirical value 0.29. I get this result inspite of the estimated adjustment costs being small in value ($c_q = 0.01$).

I now look at the difference in mean investment distortions between stand-alone and business-group firms. The simulated averages of investment distortions are comparatively smaller for small stand-alone firms (Size quintiles 1 and 2) and are comparatively larger for large stand-alone firms (firm-size quintiles 3, 4 and 5). It averages about 4 percent in the lower firm size quintiles and 10-14 percent in the larger size quintiles and thus these values are fairly consistent with the data moments. The simulated difference in mean investment distortions is underpredicted for firms in size quintile 2 (data value is 1.14, simulated value is 0.94) and overpredicted for firms in size quintile 5 (data value is 1.04 and simulated value is 1.13).

The estimated mean and dispersion in external financing rate are 0.10 and 0.21 respectively. The corresponding values in the data are lower at 0.07 and 0.14. In the model, I assume a very simple specification of the financing frictions that firms face. However, in the real world, financial policies of firms tend to be more complex. Firms have a large set of financial assets available to them; they can save in cash or other liquid assets, they can issue debt of different maturities and seniorities. Introducing a better characterization of firm financing decisions might improve the model fit of the external financing rate distribution.

In the bottom section of the model, I display non-targeted simulated model moments. Firstly, we see that the dispersion in log-capital revenue productivity for has a much larger value in the data. The data values are greater than 0.70 whereas the model value is only 0.30. As shown by Midrigan and Xu (2014), these types of financing frictions can explain only a small fraction of the within-industry dispersion (i.e. within-industry capital misallocation across firms). However, the model does a good job in producing a larger dispersion value for stand-alone firms. The simulated dispersion in log-capital revenue productivity for stand-alone firms is 0.31 whereas, the corresponding value for business-group firms is 0.24. This suggests that business-group firms benefit from the capital reallocation and cashflow diversification channels that

Table 1.8: Actual Data moments and Simulated Model moments

	Data Moments	Simulated Moments
Matched Moments		
Proportion of business-group firms	0.36	0.41
Auto correlation of firm revenue	0.98	0.97
Mean investment rate	0.12	0.11
Standard deviation of investment rate	0.17	0.17
Auto correlation of investment rate	0.29	0.50
$\mathbb{E}(1+\tau_k)^{SA}/\mathbb{E}(1+\tau_k)^{BG}$ - Size 1	0.88	0.85
$\mathbb{E}(1+\tau_k)^{SA}/\mathbb{E}(1+\tau_k)^{BG}$ - Size 2	1.14	0.94
$\mathbb{E}(1+\tau_k)^{SA}/\mathbb{E}(1+\tau_k)^{BG}$ - Size 3	1.02	1.01
$\mathbb{E}(1+\tau_k)^{SA}/\mathbb{E}(1+\tau_k)^{BG}$ - Size 4	1.10	1.08
$\mathbb{E}(1+\tau_k)^{SA}/\mathbb{E}(1+\tau_k)^{BG}$ - Size 5	1.04	1.13
Mean external financing rate	0.07	0.10
Standard deviation of external financing	0.14	0.21
Additional Moments		
Standard deviation $log(R/K)$ - stand-alone firms	0.79	0.31
Standard deviation $log(R/K)$ - bus. group firms	0.73	0.24
Mean external financing rate for stand-alone firms	0.17	0.10
Mean external financing rate for business-groups	0.16	0.10
Standard deviation of external financing for stand-alone firms	0.19	0.20
Standard deviation of external financing for business-group firms	0.18	0.23
Criterion function $\mathbb{L}(\theta)$	2713200	

This table displays the statistics of interest that are matched using the model and other statistics which are not matched. The actual data statistics and the simulated model statistics are represented in the two columns above. The value of the optimized criterion function $\mathbb{L}(\theta)$ is also given in the last row. These moments are computed using the parameter values given in Table 1.9.

operate within the business-group which lower the deviations from the frictionless investment levels.

Table 1.9 contains the estimated parameter values and the corresponding standard errors. The fixed costs governing firm diversification decisions are quite high at 0.60. These high costs ensure that the model-implied proportion of business-group firms is not very high as is observed in the data. The parameter determining persistence of productivity shocks is 0.93. Productivity uncertainty is fairly sizeable, shocks to productivity are estimated to be 11 percent per year. The parameter governing convex costs is 0.01 and the estimated financing cost parameter is 0.19. The standard errors associated with these parameter estimates are low and hence, indicate that these values are estimated quite precisely.

1.5.4 Out-of-sample Predictions

Organizational size distribution of firms

I now compute the organizational distribution of firms from the estimated model and assess its fit relative to the distribution observed in the data. This is sketched in Figure 1.4. Using the

Table 1.9: Estimated Parameter values

Fixed costs	f	0.60 (0.0008)
Persistence	ρ_z	0.93 (0.0001)
Uncertainty	σ_z	0.11 (0.0050)
Adjustment cost	c_q	0.01 (0.0010)
Financing cost	ϕ_1	0.19 (0.0067)

This table displays the parameter point estimates and the corresponding standard errors in brackets. The method of indirect inference is used to estimate these parameters.

model, I find that business-group firms are under-represented in the lower and middle firm size quintiles and slightly over-represented in the largest size quintile. The estimated model predicts that the proportion of business-group firms in size quintiles 1, 2 and 3 are 6 percent, 10 percent and 17 percent respectively. In the data, however the distribution of business-group firms is almost double these values (12 percent, 20 percent and 27 percent). In the largest size quintile, business-group firms dominate the sample of firms at 72 percent according to the model and 64 percent according to the data. However, the pattern of a larger proportion of business-group firms amongst the largest firms and a smaller proportion of business-group firms amongst the smallest firms is replicated quite accurately by the model.

1.6 Conclusion

In this paper, I empirically and theoretically analyze the role of firm organizational structure in reducing the effect of market frictions. I first provide empirical evidence on capital and labor misallocation being lower across business-group firms in the Indian manufacturing sector. Here, misallocation is identified by fitting the first order conditions of a heterogeneous firm, dynamic investment model to the data. Under certain technological assumptions, the model predicts that frictions create wedges in the marginal product of factors and are thus identifiable from the sample mean and sample dispersion in factor-revenue productivity ratios. The main assumption driving this result is that production technology is identical across firms within an industry. If this assumption does not hold, then the above results would be inconsistent. Understanding how large is this inconsistency is an important question for future research work.

To explain the smaller capital misallocation for business-group firms, I develop a dual-

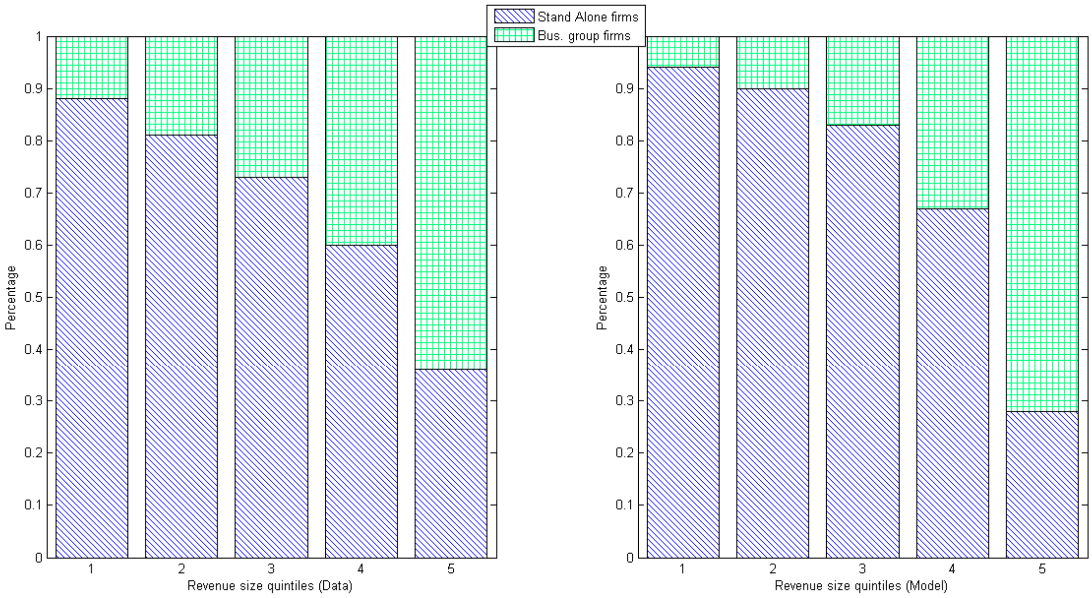


Figure 1.4: Organizational distribution of firms across different firm sizes in the Data and the Model

industry model of firm dynamics in which firm organizational structure is endogenous and investment is assumed to be irreversible, external financing is assumed to be costly. I show that the distortionary effect of these capital market imperfections is lower for business-group firms as capital is reallocated, cashflow is diversified within the group. Therefore, the model addresses the 'bright side' of business-groups and suggests that government policies which forbid the formation of diversified business-groups (example in South Korea) would be sub-optimal.

Chapter 2

Job Protection Policies and Business Group Prevalence

2.1 Introduction

A large literature establishes that diversified business-groups reduce the effect of capital market frictions faced by firms in developing countries. However, there exists very little evidence on the institutional void filled by the internal labor markets of groups when external labor markets are dysfunctional. The goal of this paper is to examine the qualitative and quantitative impact of job protection policies on the labor adjustment process of diversified business-group firms and stand-alone firms in an industry equilibrium environment.

The distortionary effect of labor market regulations on aggregate growth and development is a widely debated research topic in economics. Proponents of labor market regulations argue that these policies are necessary as they correct the effect of labor market imperfections and achieve redistribution goals within a society.[1] Several others argue that these policies interfere with the job creation/job destruction process of firms and adversely affect the economic efficiency of a country (Samuel Bentolila (1990), Hopenhayn and Rogerson (1993), Lagos (2006)). Empirically, we also find significant variation in the rigidity of employment protection laws across countries and even across regions within a country. At the country-level, the *Doing Business* database provides evidence on the nature of costs incurred by firms when dismissing workers. Using this data, I find that redundancy costs are significantly higher in developing countries.

We also know that the industrial landscape in developing countries is dominated by business-groups: a network of independent firms that are connected by family ties or formal equity ties (Masulis, Pham, and Zein (2011)). To explain this predominance, Khanna and Palepu (2000) conjecture that diversified business-groups are an optimal organizational form in countries with less developed institutions. Since their study, a large number of papers has emerged which determines whether group-affiliated firms have a relative advantage over stand-

[1] Blanchard (2002) proposes that rigid labor market regulations are an efficient institutional choice in developing countries. If firms are likely to extract rents from workers, then rigid labor laws protect workers from firing, mistreatment by firms. In contrast to developed countries, developing countries cannot use other means such as social insurance systems, contract and law enforcement to correct these labor market failures.

alone firms in developing countries and whether financial market imperfections are the source of this advantage. In this paper, I focus on imperfections in the labor market, specifically job protection policies and contrast their effect on labor accumulation decisions of stand-alone firms and business-group firms.

I first use cross-country data from 45 countries and empirically show that business-group firms are more prevalent in countries with more severe job protection policies. The indicator used in the econometric analysis is the proportion of public business-group firms across countries and is obtained from Masulis, Pham, and Zein (2011). I then collect information on the rigidity of labor markets from the World Banks *Doing Business* Database. In the univariate case, I find a positive and significant relation between these two variables. I then test whether the above relation holds in a multivariate regression framework. In addition to job protection indices, I include other determinants of business-group formation namely governance indicators, the level of financial development within countries and a political stability index. I find that in all specifications, job protection indices positively influence business-group formation. In fact, removing job protection indices reduces the goodness of fit of the econometric model from 0.79 to 0.65. The other findings obtained from this analysis are the following: prevalence of business-group firms is higher in poorer countries, countries that are poorly governed and politically unstable.

I then use firm-level data from the Indian manufacturing sector and compute indicators of labor market misallocation across business-group firms and stand-alone firms. These indicators are computed using the wedge approach of Hsieh and Klenow (2009). This approach embeds firm-specific labor market distortions (frictions) in a standard, static heterogeneous firm model and shows that distortions create wedges in the marginal revenue product of labor across firms. Further, if certain assumptions are imposed on firm production technology the approach shows that distortions can be recovered using the (within-industry) sample mean and sample dispersion in labor revenue productivity. I find that both sample mean and sample dispersion in labor revenue productivity are larger for stand-alone firms than business-group firms. Moreover, these results are consistent over the entire sample period and for industry sub-samples (i.e. results hold within the most and the least labor intensive manufacturing sector industries).

To reconcile these empirical findings, I then construct a model of firm dynamics in which the organizational structure of firms is endogenous. This model builds on the theoretical framework of Hopenhayn and Rogerson (1993) and Moscoso Boedo (2012) and quantifies the effects of job-destruction policies on firm-level labor adjustment decisions and aggregate output and productivity. I extend this model to two industries and study how redundancy costs affect the joint determination of diversification and labor accumulation policies of firms in a dual industry equilibrium environment. I also analyze the long-run impact of size dependent redundancy costs which are commonly enforced for firms in several developing countries. I numerically solve this model and calibrate the benchmark model which does not consist of any job destruction policies to establishment-level data from the US. By doing this I am implicitly assuming that establishments in the US do not incur any costs when downsizing their per-period labor stock and this is consistent with actual redundancy costs as computed for the US by the World Bank's *Doing Business Database*. After determining the unknown parameter values of the model, I perform counterfactual experiments and study the effect of firing costs where each firm has to pay workers their salary of one year upon dismissal.

Before proceeding to the results, it is important to note that the model discussed here is quite simple. I study the implications of job destruction policies when the household sector only consists of a representative consumer who supplies labor elastically and consumes the entire industrial output. A richer model environment with heterogeneous workers and heterogeneous firms would be able to capture reality and the effect of job destruction policies more accurately. Further, within the model I do not consider any firm entry or exit. Therefore, the model cannot account for the large amount of resource reallocation that arises due to the entry-exit margin and which we observe in the data. It would be interesting to see whether the results of the model would change significantly if we allowed these additional dimensions.

The main quantitative results from the model are as follows: if job destruction policies are size-independent and all firms are required to pay workers their annual salary at the time of dismissal then aggregate output drops by 5 percent and aggregate labor by 7 percent. If however, job destruction policies are size-dependent and are only applicable to firms with more than 15 workers then the aggregate effects are slightly less severe; the fall in aggregate output and labor are 4 and 5 percent respectively. Similar to the results obtained by Hopenhayn and Rogerson (1993), the long-run effects of these policies on aggregate productivity is marginal, approximately 1 percent.

Using the model, I also find that static measures of labor misallocation increase due to these distortionary policies. A larger proportion of firms have their marginal revenue product of labor deviating from the aggregate wage level; in the benchmark model only 1 percent of the firm-years display large deviations of more than 15 percent whereas, with size-dependent and size-independent policies these proportions rise to 4 and 7 percent respectively. The cross-sectional dispersion in marginal revenue product of labor increases slightly from 0.11 to 0.13 when taxes are positive. The above set of quantitative results suggest that the aggregate effects of firing costs are more severe if they are uniformly applicable across all firms than if they are only applicable for the larger firms of the economy.

Misallocation is generated within this model as high firing costs impede the reallocation of labor that occurs from high productive firms to less productive firms in the economy. Since, all firms survive within the model and the entry-exit margin is ignored in our basic framework, I expect the quantitative results as computed above to be a lower bound on the aggregate output, labor and productivity losses. The effect of job destruction policies on aggregate variables and misallocation would be more binding if firms can enter and exit. For all of the following analysis, I assume that labor is the only factor used in production and firms do not face any frictions with respect to their capital accumulation decisions. I consider this model specification as it simplifies the analysis and reduces the total time that is required for numerically solving the model.

The remainder of the paper is organized as follows. Section 2 provides the empirical motivation for the paper. I first give univariate and multivariate evidence on the cross-country determinants of business groups and the effect of country-level job destruction policies on these country-level statistics. I then use firm-level data from the Indian manufacturing sector and compute static labor misallocation measures for stand-alone and business-group firms using the wedge approach. Section 3 provides a broad overview of the labor market institutions and job protection policies that have been enforced by the governments of developing countries like Sri Lanka, India and Indonesia. Section 4 outlines a general equilibrium, dynamic theoretical model of heterogeneous firms in which firms choose their organizational structure and labor decisions while being exposed to the economy's job protection policies. I show that these policies endogenously generate labor misallocation across firms and a stationary distribution of stand-alone and business-group firms. Sections 5 and 6 describe the numerical approach that is used to solve the model, calibration of the model using establishment-level data from the US, decision rules of agents in the model economy and the cross-sectional/aggregate effects of job protection policies. Section 7 concludes.

2.2 Empirical motivation

2.2.1 Cross-country evidence - Determinants of business-groups and job protection index

In this section, I use cross-country evidence to empirically test the hypothesis that business group firms are more prevalent in countries that have greater employment protection. I first provide information about the different data sources that I use to calculate group statistics and the severity of job protection policies. I then present univariate evidence on the relation between these two variables. Finally, I show that this relation is robust to the inclusion of other possible determinants of business groups by displaying results from a multivariate regression framework.

Data Source

Cross-country prevalence of business-group firms

Firstly, information on the cross-country prevalence of business groups is obtained from Masulis, Pham, and Zein (2011). I compute group statistics from their sample as they construct business groups over a much broader range of countries. Their group construction procedure provides information on 2,763 firms belonging to 875 family-controlled groups from 45 countries. In contrast, papers such as Khanna and Palepu (2000), Claessens, Djankov, and Lang (2000), Faccio, Lang, and Young (2001) either focus on business group firms within a single country or across a much smaller sample of countries.[2] The indicator that I use for the following econometric analysis is the proportion of public firms belonging to business groups.

Ownership information on business groups is not easily available, therefore, the authors use several steps to construct business groups. They first obtain ownership information for a preliminary sample of firms from the *Osiris* database from Bureau Van Dijk and the *Worldscope* database from Thomson Reuters. If ownership data is missing or omitted for any firms, then

[2] Khanna and Palepu (2000) look at public business-group firms in India. Faccio, Lang, and Young (2001) obtain ownership information on 5,897 public firms from 9 East Asian countries and 5 West European countries for the years 1992 to 1996. They find that approximately 47 percent of firms in their sample are group-affiliated at the 20 percent cutoff level.

they fill these gaps by manually searching ownership data from other sources namely Dunn and Bradstreets *Who Owns Whom* database, Thomson Reuters *OneSource* database, *LexisNexis*, *Factiva* and country-level stock exchange websites. This initial stage gives them ownership data for 28,039 public firms for the year 2002.

For each firm, they then define and identify the controlling shareholder to be the largest shareholder who owns at least 20 percent of the firm's voting rights. If the largest shareholder also holds the CEO or board chairman positions then, he/she is defined as a controlling shareholder at the 10 percent threshold level. They also account for the cases where the controlling shareholder is not clearly visible and control is spread over multiple entities (i.e. cross-holding structures or pyramidal forms are used within groups). For these cases, they collect information on the fragmented ownership blocks and determine whether any common links exist between these blocks. They then determine whether the controlling shareholder is a family or not.

Firms are thus said to belong to a business group if all the public firms within the group share the same controlling shareholder.

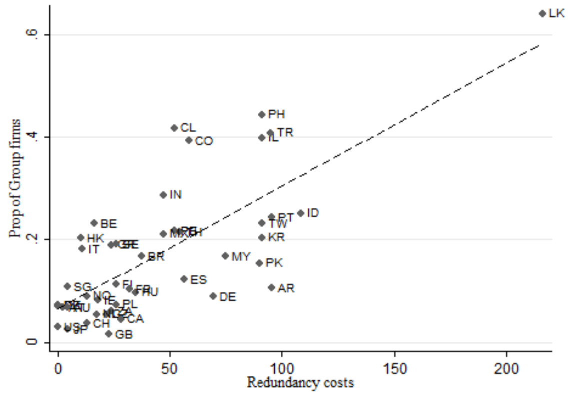
Job protection index

I use data on the stringency of labor market regulations from the World Bank's *Doing Business Database*. Since, historical data on labor market regulations are unavailable for most countries prior to 2006, I use data for the year 2006. In doing this, I assume that labor market regulations were constant over the period 2002-2006 and no country-wide reforms were made. This step gives me data for 44 countries except Venezuela.

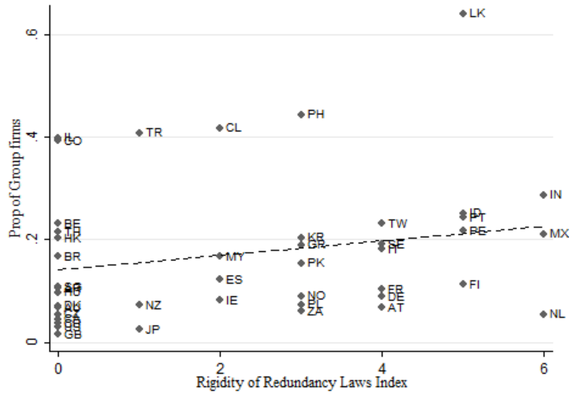
I use two indices reported in the database that measure the extent of labor market rigidity in countries. Firstly, I use the monetary costs incurred by a firm when dismissing workers. Monetary costs are computed by adding the 'notice period for redundancy dismissal after 20 years of continuous employment' and 'severance pay for redundancy dismissal after 20 years of continuous employment'. Its unit is in salary weeks. Secondly, I construct the rigidity of redundancy laws index using 6 components namely: is redundancy allowed as a basis for terminating workers, are third party notifications and approvals necessary to dismiss one/many redundant workers, is retraining necessary prior to dismissal and are any priority rules applicable for dismissals and reemployment. Its value ranges from 0 (least rigid) to 6 (most rigid). Both these indicators capture different aspects of job protection policies that are advocated at the country-level. Therefore, in the multivariate analysis, I use the principal component of these two indicators and refer to it as the Job protection index.

Univariate Evidence

In the figure, two graphs are plotted. 2.2(a) displays the scatter plot and the fitted values for the relation between proportion of business-group firms across countries and the dismissal costs incurred by firms. Whereas 2.2(b) plots proportion of business-group firms against the second indicator of job protection, i.e. rigidity of redundancy law. From both figures, we see that there exists a positive relation between job protection policies and business group prevalence.



(a) Redundancy costs



(b) Rigidity of redundancy law

Figure 2.1: Univariate cross-country evidence on business-groups and job protection costs

However, this relation is much steeper for dismissal costs and flatter for the redundancy law index. The correlation coefficient between these two indicators and the proportion of business group firms are 0.75 and 0.22 respectively and these are significant at the 5 percent level.

The proportion of business-group firms is reported to be largest (approximately 40 percent) in Sri Lanka, Chile, Turkey and Philippines and the lowest (less than 3 percent) in UK, Japan, US and Canada. The mean proportion of business-group firms across countries is relatively high at 17 percent.

Redundancy costs are largest for firms in Sri Lanka and Indonesia. In these countries, firms are required to pay 217 and 108 salary weeks of pay prior to dismissal of a worker who has been consistently employed for more than 20 years. In contrast to these countries, firms in US, New Zealand and Denmark are not required to pay any dismissal costs. The mean value of monetary costs across countries is 45 and the median is 30 salary weeks.

Redundancy law is most rigid in Mexico, India and Netherlands. The law index takes value 6 in each of these countries. However, the law index is least rigid for a significant number of countries (16 countries). The law index is only slightly negatively correlated with the income of a country but, redundancy costs are negatively and significantly correlated with the development stage of a country.

Multivariate Evidence

Past literature has offered other explanations for the formation of business-groups across countries. I now provide information on these determinants.

(a) Morck, Wolfenzon, and Yeung (2005) argues that business groups enable controlling shareholders to extract private benefits of control from the firms belonging to the group. If groups are structured as pyramids and cross-holdings/dual-class shares are used (within the group) by controlling shareholders, then these can generate agency frictions as they lead to a separation of ownership and control. This argument suggests that business-group firms will be more prevalent in countries that have higher private benefits of control or have insufficient governance mechanisms to discipline this behavior of controlling shareholders. I follow Dyck and Zingales (2002) and use several proxies that represent the governance standards of a country. The legal protection of minority investors is measured using the 'corrected Anti-director rights index' constructed by Spamann (2010), the legal origin of a country is obtained from Rafael La Porta and Vishny (1997) and I develop a governance indicator that represents rule of law, financial disclosure within the country. I also include extralegal institutions such as diffusion of newspapers that can serve as powerful governance tools in the economy. I provide more information on the source and the formulation of these indicators in Table 2.1.

(b)Masulis, Pham, and Zein (2011) theorize that the benefits of business groups are due to their internal capital markets. If risk sharing opportunities and provision of financial support is greater within business groups then, group-affiliated firms have a financing advantage in economies with poorly developed financial markets. Therefore, this reasoning implies that group-firms should be more concentrated in countries with low supplies of capital. To measure the supply of capital in a country, I follow their approach and include country-level GDP and the national domestic savings to GDP ratio. We expect less developed financial markets to negatively affect the *GDP* of a country. A lower *Savings to GDP ratio* reduces the amount of funds available to financial intermediaries to lend.[3]

(c) I also account for the *Political stability* of the country. If politically unstable countries are more likely to expropriate foreign investors then they will also attract less foreign direct and institutional investment. Therefore, political instability can directly affect the size of a country's capital markets. Political instability can also increase the business risk that firms face. In these environments, the value of risk-sharing provided within a business group may be higher.

(d) Both hiring and firing constraints can reduce the flexibility of external labor markets and increase the value of group internal labor markets. If a firm faces a positive demand shock then it may want to increase its stock of labor. However, if hiring workers is difficult, if the firm cannot easily hire fixed-term contract workers then it may not increase its production scale and take advantage of this profitable opportunity (Bloom (2009)). In these situations,

[3]Masulis, Pham, and Zein (2011) do not use traditional measures of financial market development such as the stock market capitalization to GDP ratio, private credit to GDP ratio. As shown by Rafael La Porta and Vishny (1997), these measures are likely to be correlated with the anti-director rights, governance indicators. Therefore, multi-collinearity could result in an insignificant coefficient for the financial market development indicator(s). In contrast to the above indicators, the authors use the income of a country and the savings to GDP ratio as alternative proxies. Poorer countries would have smaller financial markets. Countries with low savings have less capital to supply to financial intermediaries which further reduces the amount of finance available for firms.

business group headquarters can reallocate labor to the industries/firms that are performing well/that are expected to perform better than the other group firms. Therefore, hiring costs can also be a potential determinant of business groups. To control for this variable I use information from the World Bank's *Doing Business Database* and construct *Difficulty of hiring indices.* The World Bank collects information on two variables which captures whether firms can easily hire contract workers to fulfill their temporary production demands. The first variable is 'Are fixed term contracts prohibited for permanent tasks?' and this takes either value 1(Yes) or 0(No). The second variable is 'What is the maximum cumulative duration of a fixed-term employment relationship (in months), including all renewals?' and its minimum value is 0 whereas its maximum value is 120. From these variables I then compute the *Difficulty of hiring indices* which are the first and second principle components of the above variables. Larger values of these indices indicate that hiring difficulties are more severe within the country.[4]

(e) Finally, I include *Takeover* an index developed by Nenova (2006). This index measures the ease with which takeovers can occur within the country. The market for corporate control also acts as a disciplining device for limiting the extraction of resources by controlling shareholders (Jensen (1988)). If agency frictions are higher within business-groups then, we should expect a lower fraction of business-group firms in countries with more investor-friendly takeover regulations.

Regression analysis

I now present the results from a multivariate regression which estimates the influence of country-level variables on the prevalence of business-group firms. These regressions are estimated using the Ordinary least squares method and the standard errors are corrected for heteroskedasticity. Table 2.2 reports the results from the regression analysis. Column (1) includes all the independent variables that were hypothesized to affect the proportion of business-group firms across countries except for difficulty of hiring indices. These include job protection indices, legal origin of countries, governance indices, indicators of financial market development and political stability. Column (2) displays the results for a regression that excludes the job protection indices. In Column (3), the legal origin of countries is not included as an independent variable. Finally in Column (4), in addition to the above regressors I also include an index that measures the rigidity of takeover regulations within countries.

We firstly see that job protections policies positively influence the formation of business-groups in countries. In columns (1), (3) and (4) the coefficients are statistically significant at the 1 and 5 percent level respectively. In column (4), when takeover regulations are added to the regression, the effect of job protection policies somewhat decreases but it continues to be significant. The fit of the model is also higher when Job protection policies are included as

[4]There may be other benefits for a firm when it hires labor from its group's internal pool of workers. If firms have asymmetric information about worker's skills then by hiring workers from the internal labor market they can reduce their informational costs. Group firms can share employee-specific information amongst each other and this can lead to better matches between skilled workers and firms. If firms have to incur training costs to make workers more productive then, within a business-group training costs can be shared so that the employee builds group-specific human capital.

Table 2.1: Description of variables

Indicator	Description and Source
Redundancy costs	Adding notice period and severance pay for redundancy dismissal after 20 years of continuous employment - *Doing Business* 2006, World Bank
Rigidity in redundancy law index	Assigned 1 if country's laws prescribe following: redundancy not allowed for terminating workers, third party notifications and approvals necessary to dismiss one/many redundant workers, retraining necessary prior to dismissal, priority rules applicable for dismissals and reemployment - *Doing Business* 2006, World Bank
Job protection index 1 & 2	First, second principle components of redundancy costs and rigidity in redundancy law
Difficulty of hiring index 1 & 2	First, second principle components of following: are fixed term contracts prohibited for permanent tasks, what is the maximum cumulative duration of fixed term contracts (in months) - *Doing Business* 2006, World Bank
Legal origin	Dummy variables for countries with English common law or French civil law or German civil law traditions - Rafael La Porta and Vishny (1997)
Governance indices 1 & 2	First and second principle components of anti-director rights index (Spamann (2010)), property rights and control of corruption index (*Heritage Foundation* and *Wall Street Journal*), financial and governance transparency factors (Bushman, Piotroski and Smith (2003))
News diffusion	Number of papers circulated per 1000 people - *World Development Indicators*
Takeover	Index measures investor friendliness of takeover regulations within a country. Larger values indicate takeovers easier - Nenova (2006)
log(GDP)	Logarithm of GDP - *World Development Indicators*
Savings to GDP ratio	*World Development Indicators*, IMF *World Economic Outlook*
Political stability	*Worldwide Governance Indicators*

regressors. As shown in Columns (2) and (4) the R2 increases from 0.77 to 0.87 if the regression is estimated without country-level labor market rigidities.

Legal origins of a country seem to matter to an extent. Business-groups are less likely to be prevalent in countries with English common law, German civil law origin and are more likely in countries with a French civil law origin. However, these coefficients are not consistently significant in all regressions.

Poorly governed countries are more likely to have a higher proportion of business-group firms. Governance Index 2 which is the second principle component of all the legal governance indicators is seen to be significant in columns (1) and (3). The extralegal governance institutions i.e. the diffusion of newspapers and the ease of takeover market regulations do not seem to influence the dependent variable.

Moreover, we find that prevalence of business-group firms is greater in countries which are poorer and are less stable politically. Therefore, financial development is also an important factor which determines the formation of business groups across countries.

In all the regressions given in Table 2.2, we see that the difficulty of hiring index is statistically significant and the model fit increases when these variables are added to regressions. However, the sign of the estimated coefficient does not fit our hypothesis. The analysis below predicts that countries with more severe hiring difficulties will have a lower prevalence of business-group firms instead of a larger prevalence of business-group firms and hence, it is inconsistent with our earlier story.

Table 2.2: Cross-country determinants of business-group prevalence and Job protection policies

Dependent: Prop of business-group firms				
	(1)	(2)	(3)	(4)
Job protection index 1	0.048***		0.051***	0.047**
	(0.01)		(0.01)	(0.02)
Job protection index 2	0.029		0.031	0.041*
	(0.03)		(0.02)	(0.02)
English common law	-0.060	-0.106**		-0.117**
	(0.05)	(0.05)		(0.05)
German civil law	-0.125***	-0.114		-0.142*
	(0.04)	(0.09)		(0.08)
Scandinavian civil law	-0.103*	-0.051		-0.034
	(0.05)	(0.09)		(0.10)
Governance index 1	0.021	-0.004	-0.009	-0.022
	(0.02)	(0.02)	(0.02)	(0.02)
Governance index 2	-0.028**	-0.024	-0.035**	-0.014
	(0.01)	(0.01)	(0.01)	(0.02)
News diffusion	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
log(GDP)	-0.037***	-0.044***	-0.042***	-0.037***
	(0.01)	(0.01)	(0.01)	(0.01)
Savings to GDP	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Political stability	-0.076***	-0.093**	-0.043**	-0.034
	(0.03)	(0.03)	(0.02)	(0.04)
Takeover				0.057
				(0.20)
Difficulty of hiring index 1		-0.041**	-0.032**	-0.057***
		(0.02)	(0.01)	(0.02)
Difficulty of hiring index 2		-0.015	-0.000	-0.022
		(0.02)	(0.02)	(0.02)
R2	0.78	0.77	0.79	0.87
(No. of observations)	(36)	(36)	(36)	(31)

Table 2 presents regressions of proportion of business-group firms across countries on country-level variables. The construction of the regressors and their data source are described in Table 1. The dependent variable is the proportion of business-group firms in a country. Column (1) includes all the hypothesized regressions except for Difficulty of hiring indices. Column (2) includes all variables except for the Job protection indices. In Column (3), the effect of Legal origin of a country on business-group prevalence is eliminated. Column (4) includes all regressors including the Takeover variable which is a variable that measures the investor friendliness of takeover regulations within a country. All regressions are estimated using the OLS method. The fit of the regression, R2, and the number of countries in the sample are also reported. Standard errors obtained from the regression are corrected for heteroscedasticity. Robust standard errors are given in parenthesis. $*$, $**$ and $***$ denotes significance at the 10, 5 and 1 percent level respectively.

2.2.2 Firm-level evidence from India - Labor market misallocation

In this section, I use Indian firm-level data and provide some evidence on the extent of labor market misallocation between stand-alone and business-group firms. The misallocation indicator, here, is derived following the wedge-approach of Hsieh and Klenow (2009). This approach assumes that production technology is Cobb Douglas, is identical across firms and associates all the cross-sectional dispersion in the labor revenue productivity ratio to idiosyncratic firm-sepcific distortions. These distortions generate misallocation as all firms do not face the same 'cost' of labor when they make their labor rental decisions.

Misallocation using wedge approch

Consider a closed economy which lives for a single period and consists of heterogeneous firms. Firms differ in their productivity shocks and possibly in their labor market distortions. These distortions are taxes which affect labor hiring decisions and are a reduced-form representation of all types of labor market frictions that firms face. Since, the focus of this section is on labor market misallocation, the model is silent on capital market frictions faced by firms. I assume that capital is optimized out of the problem and firms face no frictions in their capital markets.

The economy consists of S industries and a continuum of firms in each of these industries. Firms in every industry can either be stand-alone or business-group firms (SA or BG). I assume that the fraction of stand-alone firms in each industry is M_s.

Firm revenue is produced according to a decreasing returns to scale production function i.e. we are assuming that firm i in industry s has some market power in producing its differentiated good. If Z_{si} is the idiosyncratic productivity of firm i and if L_{si} is labor hired by firm i then, firm revenue is produced according to,

$$R_{si} = Z_{si} L_{si}^{\alpha_{ls}} \tag{2.1}$$

Assumption 4. *Labor share parameter $\alpha_{ls} < 1$ can differ across industries but, is identical for firms belonging to industry s.*

Assumption 4 is associated with firm production technology. According to this assumption all firms in industry s are characterized by the same technology. While this assumptions is restrictive, it is commonly used in this literature.[5]

Assumption 5. *In this economy, firms in every period face labor market distortions. Distortions are assumed to be firm-specific and affect the cost of rented labor for firm i. It is denoted by the variable τ_{Lsi} and I assume that it follows a lognormal distribution with the underlying parameters depending on the industry s and type $t \in \{SA, BG\}$ of firm i.[6] This can be expressed*

[5] Note that if there was heterogeneity in factor shares within industry s, then, this would also generate wedges in the first order conditions and these would be mismeasured as distortions. In my empirical analysis, I also compute the mean distortions between similarly-sized stand-alone and business-group firms. This should control for this measurement bias, as technological differences are more likely to arise between large and small firms instead of across similarly-sized firms within industry s.

[6] As long as distortions are i.i.d. shocks, the identification is robust to the use of other distributions for distortions as well.

as,

$$ln(1+\tau_{Lsi}) \sim^{i.i.d.} \mathbb{N}(\mu^t_{Ls}, \sigma^t_{Ls}), \quad t \in \{SA, BG\} \tag{2.2}$$

Therefore, the optimization problem of the firm is represented as,

$$max_{L_i}\,[Z_{si}L_{si}^{\alpha_{ls}} - W(1+\tau_{Lsi})]$$

Solving for labor from its F.O.C. I get,

$$\alpha_{ls}\frac{Z_{si}L_{si}^{\alpha_{ls}}}{L_{si}} = W(1+\tau_{Lsi}) \tag{2.3}$$

$$\alpha_{ls}\frac{R_{si}}{WL_{si}} = (1+\tau_{Lsi}) \tag{2.4}$$

where R_{si} denotes revenue of Firm i. Therefore, firm-specific labor distortions can be directly imputed from known variables. The above equation predicts that the after-tax (after-distortion) marginal revenue product of labor is equal across firms. If distortions were zero or identical across firms, then there would be the dispersion in the marginal products of labor across firms would be equal to zero. However, firm-specific distortions generate positive dispersion in the labor revenue productivity ratio and generate misallocation of labor across firms.[7]

From equation 2.4, we can derive the mean and dispersion in labor market distortions for stand-alone firms and business-group firms. This is given in the following proposition,

Proposition 2. *If labor distortions for firms belonging to type $t = \{SA, BG\}$, industry s are i.i.d. and follow a lognormal distribution, then the population mean of labor distortions is asymptotically proportional to the sample mean labor revenue productivity ratio*

$$\mathbb{E}^t_s(1+\tau_{Lsi}) \simeq \alpha_{ls}\bar{\mathbb{E}}^t_s\left[\frac{R_{si}}{WL_{si}}\right] \tag{2.5}$$

and the population dispersion of labor distortions is asymptotically proportional to the sample dispersion of the labor revenue productivity ratio

$$\Sigma^t_s\Big[ln(1+\tau_{Lsi})\Big] \simeq \bar{\Sigma}^t_s\left[ln\left[\frac{R'_{si}}{WL'_{si}}\right]\right] \tag{2.6}$$

Proof in the Appendix.

Data Source

Firm-level data for India is drawn from the Prowess database prepared by CMIE, Center for Monitoring the Indian Economy. This database records detailed financial, ownership and industry information on large public and private firms that operate within the formal Indian sector across a wide range of industries manufacturing, services, wholesale and retail trade. The firms included in the database account for more than 70 percent of industrial output, 75 percent of

[7]Assumption of a Cobb-Douglas production functions implies that the labor revenue productivity ratio is proportional to the average and hence, marginal product of labor. If labor share is assumed to be constant within each industry and firms do not face any distortions then, the dispersion in labor revenue productivity is predicted to be equal to zero according to the above model.

corporate taxes, and more than 95 percent of the excise taxes collected by the Government of India.

The advantage of using this database is that unlike the cross-sectional plant-level ASI (Annual Survey of Industries) database used in Hsieh and Klenow (2009), Prowess stores panel data on firms. In contrast to most of the commonly used datasets in academic literature, (*Compustat Global, Worldscope*), the dataset covers a large fraction of private firms operating in the Indian economy. About two-thirds of the firms in the raw dataset consist of private firms. Finally, it tracks ownership information on firms and identifies the firms that belong to business-groups. This aspect of the database makes it highly appropriate for my analysis.[8]

I restrict my sample to stand-alone and business-group firms that operate within the manufacturing sector between 1995-2013. In every year of this sample period, I drop firm-years that belong to business groups of (firm) size less than two. The variables that I use are firm value added, wage bill, capital stock, along with the 2-digit industry that firms belong to. Capital stock is measured empirically using a firm's reported gross fixed assets and computed using the Perpetual Inventory method.

For the following estimation procedure, capital and labor intensities are specified at the 2-digit Indian industry level and are equal to $\alpha_{ks} = (1-\mu)(1-\beta_s)$, $\alpha_{ls} = (1-\mu)\beta_s$. Here, μ denotes the markup which is assumed to be constant across all firms and across all industries. β_s is the labor share value for industry s and like Hsieh and Klenow (2009), I assume that these values are equal to the values for the corresponding 2 digit industry in the US.[9]

I match Indian and US manufacturing industries at the 2-digit level and use data reported by the US Bureau of Economic Analysis to compute labor share β_s using the variables Gross Value Added GVA_s and Labor Compensation $COMP_s$.
Labor revenue productivity and capital-intensity of firms are empirically defined as,

$$\frac{R_{it}}{L_{it}} = \frac{ValueAdded_{it}}{WageBill_{it}} \tag{2.7}$$

$$\frac{K_{it}}{L_{it}} = \frac{Capitalstock_{it}}{WageBill_{it}} \tag{2.8}$$

To ensure that the identification results are robust and not driven by extreme observations, firm-years are dropped that have productivity values in the top and bottom 5 percentiles. All the above variables have been deflated into real values - firm (final good) industry deflators are used to deflate value added, wage bill variables, whereas the capital goods deflator is used to deflate capital stock and investment variables.

These restrictions give me an unbalanced panel of approximately 23,000 business-group

[8]Unlike Korean chaebols, there is no formal determination of Indian business groups. Group structure and ownership stakes of the controlling family across different firms are not required to be disclosed except for publicly traded firms. Therefore, the database creates these firm-group matches by collecting information from firm annual reports and by continuously monitoring the announcements made by firms. This firm-group matching scheme is quite robust and has been previously used in Khanna and Palepu (2000), Gopalan, Nanda, and Seru (2007) and Alfaro and Chari (2014).

[9]This assumption implies that firms in US and Indian manufacturing industries employ the same production technology and any observed variation in capital and labor revenue productivity ratios is solely due to differences in firm-level distortions. As they argue, in the absence of this assumption, it is not possible to separately identify the average factor elasticity for the Indian industry from the average factor distortions that firms in that industry face.

firm-years and 49,000 stand-alone firm-years. The proportion of private firms within this sample is quite high - they comprise 54 percent in the entire sample, 39 percent amongst business-group firms and a larger 61 percent amongst stand-alone firms.

I also segregate firms belonging to the most and the least labor intensive manufacturing sectors. I use the labor shares that are computed from US aggregate data for this classification. The two-digit industries that report the highest labor share are the most labor-intensive industries and the two-digit industries with the lowest labor share are the least labor-intensive industries. I provide information on these industries are their associated labor share values in the appendix. There is a slightly smaller concentration (65 percent) of stand-alone firms in the most labor-intensive manufacturing industries and slightly higher concentration (70 percent) in the least labor-intensive manufacturing industries.

Indicators of Labor market misallocation

Dispersion in labor-revenue productivity

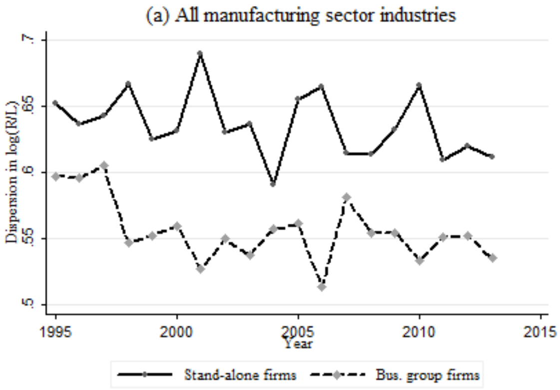
In the following graphs, I provide evidence on the evolution of labor market misallocation in the Indian manufacturing sector. I plot the dispersion in (log) labor revenue productivity for stand-alone firms and business-group firms over the sample period 1995-2013. In Figure 2.3(a), the dispersion value is plotted using the entire sample of manufacturing firms. In figures 2.3(b) and 2.3(c), the results are reported only for firms belonging to the most labor intensive and the least labor intensive manufacturing sectors.

From the graphs, we see that the dispersion values are large and quite volatile. It ranges for 0.5-0.7 over the entire sample period. The wedge approach predicts that within-industry dispersion in labor revenue productivity is an indicator of misallocation of labor across firms. This prediction along with the graphical evidence imply that misallocation is larger across stand-alone firms than business-group firms. In other words, larger frictions are responsible for impeding the labor reallocation process across stand-alone firms. The labor decisions of the most efficient stand-alone firms are distorted to a greater extent than the labor decisions of business-group firms.

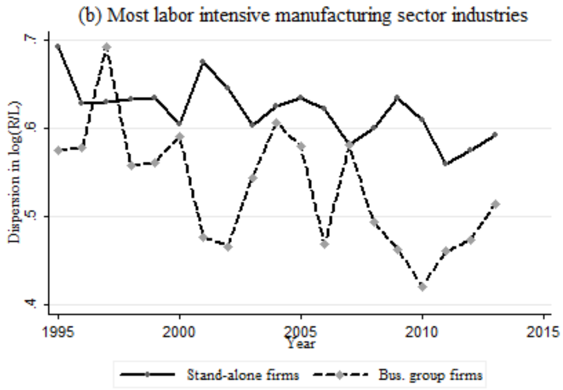
These results are robust for sub-samples of firms as well. Except for an initial period, the relation of higher misallocation for stand-alone firms is observed both in the most-labor intensive and the least labor-intensive manufacturing sectors. The difference between the dispersion indicator however, seems to be larger for the least-labor intensive industries. This observation intuitively makes sense. If labor market frictions are larger (relative price of labor is larger) for stand-alone firms and if the technological intensity of firms production function is endogenous, then stand-alone firms are more likely to choose more capital intensive technologies. Now, stand-alone firms in the least labor intensive industries have a higher capacity to switch to more capital intensive production functions and therefore, their under-investment in labor is even higher.

Mean labor distortions

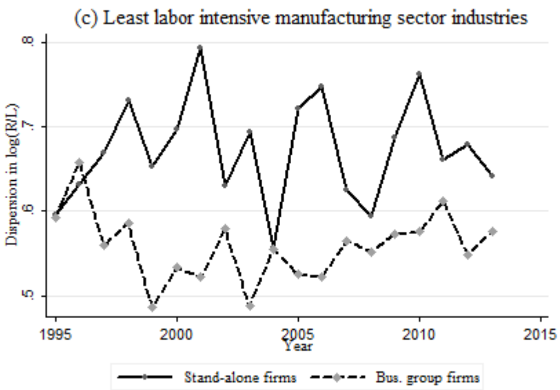
In Table 2.3, I report the mean labor distortions and the mean capital intensity for stand-alone



(a)



(b)



(c)

Figure 2.2: Dispersion in log labor productivity in the Indian manufacturing sector over the sample period 1995-2013

and business-group firms. Across most size quintiles and for various sub-samples of firms, we find that stand-alone firms are more likely to display larger mean labor distortions.

Therefore, the empirical findings of this section can be summarized as,

1. Using a multivariate regression framework, I show that business group firms are more likely to be prevalent in countries with more rigid job protection policies. The effect of rigid job protection policies is statistically significant and is unaffected by the inclusion of other determinants of business-groups.

2. The within-industry dispersion in labor revenue productivity is larger for stand-alone firms than business-group firms. This relation holds over time, over the entire sample of manufacturing sector firms and for sub-samples of firms.

3. I control for firm size and firm industry, and find that mean labor distortions are (mostly) larger for stand-alone firms than business-group firms.

2.3 Overview of Labor market institutions

In developing countries, job protection policies tend to be too complex and restrictive. Further, enforcement of these laws is imperfect and oftentimes firms find various ways to circumvent these regulations. There are several procedures and costs that firms have to bear while dismissing workers and compliance occurs in an ad-hoc fashion by government officials.

Table 2.3: Mean labor distortions and mean capital intensity for firms belonging to the Indian manufacturing sector over the sample period 1995-2013

Panel A: All manufacturing sector industries				
	$\mathbb{E}(log(1+\tau_l))$		log(K/L)	
	Stand-alone firms	Bus. group firms	Stand-alone firms	Bus. group firms
All firm sizes	1.27	1.16	2.30	2.24
Size 1	1.00	0.85	2.72	2.37
Size 2	1.20	1.03	2.37	2.38
Size 3	1.31	1.18	2.24	2.23
Size 4	1.40	1.31	2.16	2.12
Size 5	1.43	1.39	2.09	2.03
Panel B: Most labor intensive industries				
	$\mathbb{E}(log(1+\tau_l))$		log(K/L)	
	Stand-alone firms	Bus. group firms	Stand-alone firms	Bus. group firms
All firm sizes	1.39	1.31	2.15	2.15
Size 1	1.22	0.98	2.68	2.00
Size 2	1.20	1.27	2.23	2.46
Size 3	1.48	1.34	2.34	2.12
Size 4	1.44	1.50	2.07	1.98
Size 5	1.43	1.41	1.85	1.75
Panel C: Least labor intensive industries				
	$\mathbb{E}(log(1+\tau_l))$		log(K/L)	
	Stand-alone firms	Bus. group firms	Stand-alone firms	Bus. group firms
All firm sizes	0.87	1.01	2.54	2.43
Size 1	0.63	0.61	2.51	3.21
Size 2	0.90	0.99	2.81	2.51
Size 3	0.80	0.58	2.47	2.11
Size 4	1.02	0.86	2.41	2.26
Size 5	1.67	1.36	2.54	2.55

In the table, I compute the mean labor distortions and the mean capital intensity across stand-alone and business-group firms in the Indian manufacturing sector for the sample period 1995-2013. Mean labor distortions are computed using the wedge approach of Hsieh and Klenow (2009). In Panel A, I report values for firms belonging to the entire universe of firms. In Panels B and C, the first moments are reported for the most and the least labor intensive manufacturing sectors.

These policies not only dis-incentivize firms from participating in the job creation/job destruction process but they also fall short of their intended goal of providing indirect insurance to workers. In this section, I focus on labor market institutions in Sri Lanka, India and Indonesia as these countries have been identified with the most rigid job protection policies.

Sri Lanka

In Sri Lanka, the main policy governing worker protection is TEWA (Termination of Employment of Workman Act) which was introduced in 1971.[10] It is one of the costliest severance pay systems in the world. At the time of introduction, its stated objective was to reduce unemployment by increasing the cost of dismissing workers by firms. This law applies to all firms who have more than 15 workers, applies to all workers who have been employed for more than 180 days and applies to cases of non-disciplinary termination of employment. In order to dismiss a worker or many workers, a firm is required to provide evidence and obtain approval from the Commissioner General of Labor (CGL). Prior to 2003, consent from the CGL was also required to determine the severance payment of the dismissed worker(s). After 2003, according to the Doing Business Database, firms had to pay workers for 217 salary weeks. This statistic is for workers who have been employed continuously for more than 20 years. The dismissal process is costly for firms as workers have to be paid over the inquiry period irrespective of the amount of work done by them and the average duration of this period tends to be approximately 10 months.

As a result of these high turnover costs, very few firms in Sri Lanka applied to the CGL to dismiss workers, most of the cases were settled voluntarily between the firm and the worker(s) through negotiated retirement packages. These negotiated packages offered are huge and although the law applies to only non-disciplinary termination of employment, even inefficient and incompetent workers are paid generously.

Firms can avoid paying these dismissal costs by using contract workers or by outsourcing jobs (contract workers are not under the purview of these laws). However, we have no information that assesses to what extent firms use these outside options. Labor market regulations are so stringent that they are cited as one of the five most severe frictions faced by firms in the Sri Lankan urban manufacturing sector.

India

In India, the main legislative regulation governing the formal industrial labor market policies is the Industrial Disputes Act (IDA) of 1947. The act was designed so that workers would receive some job security and some protection against exploitation by firms. In the event of industrial disputes, the act specifies several procedures that have to be followed and prescribes the division of power between the different actors: unions, firms, government, courts and workers. This legislation is under the joint jurisdiction of both the federal and the state governments. As documented by Besley and Burgess (2004), after independence various states have passed amendments to the IDA which has resulted in significant variation in labor market

[10]For more information about TEWA, please refer to the detailed description given in Abidoye, Orazem, and Vodopivec (2009))

rules across states. They also find evidence for improved investment, output and productivity outcomes for states that amended the regulations in a pro-employer direction.

The key draconian and controversial aspect of the IDA is the requirement that firms in India with more than 100 workers obtain permission from state governments prior to permanent retrenchment or temporary layoff of workers. Prior to 1976 no size restrictions had been enacted/specified by this legislation, however following an amendment in 1976, this law only applied to firms with more than 300 workers. In 1982, coverage of the law was increased to smaller firms i.e. firms with more than 100 workers. The consequences of not adhering to these laws are fines that the employer has to pay or sometimes even prison sentence (Fallon and Lucas (1993)). Oftentimes the government would deny permission to close down factories even if there were unproductive and these factories would be declared as sick units (Topalova (2010)). The above firing procedures are only applicable for permanent workers not contract workers. Also, these procedures are not applicable if industrial workers opt for voluntary retirement. Therefore, to avoid this lengthy legal arbitration process, firms mostly adjust their labor out of court by offering very high voluntary retirement packages to industrial workers.

Indonesia

During Suhartos New Order rule, Indonesia witnessed high economic growth and industrialization.[11] However, throughout this three-decade period Suharto and his family members also amassed a significant amount of personal fortune. There is a large amount of evidence which suggests that political corruption, nepotism and business cronyism was an intrinsic part of his rule.[12]

As far as labor market policies were concerned, social and economic interests of industrial workers were completely neglected by Suhartos governments. In the name of industrial expansion, workers had few labor rights and low bargaining power. They had poor living standards and often were forced to work 120-hour weeks. Workers could not freely organize themselves into trade unions as the law officially recognized only one trade union, SPSI, which had very close links with the government and did not really represent or support workers demands. In the last years of Suhartos rule and in the years following it, several labor market reforms were introduced in Indonesia. The country saw increased trade union activity. The minimum wage and the level of severance pay increased to give greater protection to workers.

Labor market regulation and enforcement has been very extensive in the post-Suharto era. Although, government ministries have often tried to amend these legislations, stiff union opposition prevented them from doing so. These rigid labor market regulations may have also resulted in economic growth, investment activity and job creation slowing down in the Indonesian manufacturing sector.[13]

[11] The economic policies that his government followed focused on an export-oriented growth strategy; the industrial base expanded, trade was liberalized and labor intensive manufacturing was encouraged.

[12] These structural flaws led to large capital outflows from Indonesia during the 1997 Asian Financial Crisis. During the crisis, the economic collapse that Indonesia faced was so severe that Suharto was forced to end his rule and resign from the post of president in 1998 in response to massive public pressure.

[13] For more information about labor market policies during the Suharto and post-Suharto regime, please refer to The Political Economy of Reform: Labour after Soeharto Chris Manning in Aspinall and Fealy (2010).

2.4 Model with endogenous business-group formation

In this section I develop a dynamic, general equilibrium model which examines the effect of job destruction policies on the organizational decisions of firms. This framework is a modified version of Hopenhayn and Rogerson (1993) and Gomes and Livdan (2004). Like Hopenhayn and Rogerson (1993), I study the effect of redundancy costs on the labor accumulation decisions of firms and on aggregate variables like consumption, output and productivity. In contrast to their single-industry framework, I introduce two industries within the model economy and embed endogenous diversification decisions of firms (Gomes and Livdan (2004)).

I now describe the main features of the model. I consider an infinitely-lived economy which consists of two industries, a representative household and a continuum of heterogenous firms. In each period, there are two types of firms in the economy: stand-alone firms and diversified business groups. Stand-alone firms only produce output good of a single industry whereas diversified business-groups produce goods of both industries. Firms output for each industry is produced using a stochastic, decreasing returns to scale technology which uses labor as an input. The only sources of uncertainty in the benchmark model are firm's productivity shocks for each industry.

Post production, firms decide their labor accumulation policies and their organizational structure for the next period.[14] Motivated by the empirical evidence in the previous sections, I assume that firms have to pay linear adjustment costs when dismissing workers. Moreover, two specifications are considered: adjustment costs can either be size independent or size dependent. These non-convex costs generate periods of inaction for firms and distort their labor accumulation decisions.

Finally, the representative household in the economy has a limited role to play. It consumes industrial goods, supplies labor, receives aggregate redundancy payments, wage payments and profits produced by the continuum of firms. The model is solved for the stationary steady state in which all markets clear, the equilibrium wage and the distribution of firms over the productivity-labor-organizational form space are constant.

2.4.1 Production decisions

Each period in the economy corresponds to a year. The economy consists of two industries - 1 and 2. Firm i enters the period as a stand-alone firm or a diversified business-group. If firm i is a stand-alone firm then it allocates its labor n_i to only one industry (industry 1 or 2). However, if it is a business-group then it allocates its labor across both industries.[15]

Firm i at the beginning of the period, observes its productivity shocks for both in-

[14] Factors and firm structure are chosen one period in advance by firms.

[15] While stand-alone firms only produce goods of one industry, business-groups are diversified entities that produce goods of both industries. Since, most business-groups feature high levels of horizontal diversification, this assumption seems appropriate. In the model, firms cannot diversify across more than two industries whereas in reality, most business groups/conglomerates operate over multiple industries. While extension of the model to more than two industries would capture this fact better, it would also make the computational problem more complex to solve. Also, as the model does not include any strategic reasons due to which firms diversify, inclusion of multiple industries would not change the underlying reasons why firms diversify and only make the results only stronger.

dustries and I denote these as $Z_i = (Z_{1i}, Z_{2i})$.[16] The logarithm of these shocks are assumed to follow a VAR(1) process,

$$\begin{bmatrix} log(Z_{1i}) \\ log(Z_{2i}) \end{bmatrix} = \begin{bmatrix} \rho_z & 0 \\ 0 & \rho_z \end{bmatrix} \begin{bmatrix} log(Z_{1i,-1}) \\ log(Z_{2i,-1}) \end{bmatrix} + \begin{bmatrix} \epsilon_{1i} \\ \epsilon_{2i} \end{bmatrix} \tag{2.9}$$

with variance-covariance matrix given by,

$$\begin{bmatrix} \epsilon_{1i} \\ \epsilon_{2i} \end{bmatrix} \sim \mathbb{N}(0, \Sigma)$$

Therefore, I allow for correlation to be zero or non-zero between the two industrial productivity shocks. I denote the conditional probability distribution function for the above VAR(1) process by $P(Z'|Z)$.

Predetermined state variables for firm i are its labor stock n_i and the fraction of labor, θ_i, that it allocates to industry 1. If $\theta_i = 1$ or $\theta_i = 0$, then firm i is a stand-alone firm in industry 1 and 2 respectively and if $\theta_i \in (0,1)$ then it is a business-group.

Production possibilities for firm i in each industry are given via a decreasing returns to scale production function,

$$F(Z_{1i}, n_i, \theta_i) = Z_{1i} \left(\theta_i n_i\right)^{\alpha} \tag{2.10}$$

and,

$$F(Z_{2i}, n_i, 1-\theta_i) = Z_{2i} \left((1-\theta_i) n_i\right)^{\alpha} \tag{2.11}$$

In the above specification, we see that the prices of both industrial goods are equal and normalized to 1. This implies that both industrial goods are perfect substitutes for the representative household. After production of industrial revenue, firm i takes the wage W as given and pays its labor costs. It also pays fixed operating costs which are assumed to be higher for business-groups. As shown by Gomes and Livdan (2004), this assumption ensures that not all firms choose to diversify and a non-zero measure of stand-alone firms arises in the stationary equilibrium. Profits for firm i are thus given by,

$$\pi(Z_{1i}, n_i, \theta_i; W) + \pi(Z_{2i}, n_i, 1-\theta_i; W) = F(Z_{1i}, n_i, \theta_i) + F(Z_{2i}, n_i, 1-\theta_i) - W n_i - f - f\mathbb{I}_{\theta_i \in (0,1)} \tag{2.12}$$

According to the above equation, workers have zero bargaining power and the firm (firm shareholders) enjoys all the surplus from production.

2.4.2 Organizational and Labor accumulation decisions

After producing industrial profits, firm i then chooses its organizational structure for the following period, i.e. θ_i'. The organizational choices for firms are such that, a stand-alone firm can either remain its own industry or it can diversify to both industries. Business groups however, have more organizational choices. They can stay diversified or can become stand-alone firms in

[16] There is no learning in the model and irrespective of whether the firm is stand-alone or a business-group it observes its efficiency in both industries.

any one of the two industries. These choices are thus represented as,

$$\theta_i' \in \begin{cases} \{1\} \cup (0,1) & \text{if } \theta_i = 1 \\ \{0\} \cup (0,1) & \text{if } \theta_i = 0 \\ \{0\} \cup \{1\} \cup (0,1) & \text{if } \theta_i \in (0,1) \end{cases}$$

The first two cases are organizational choices for stand-alone firms in industries 1 and 2, and the third case is the choice for a diversified business-group.

2.4.3 Job protection policies

Conditional on its organizational choice θ_i' for the next period, it also decides to hire or dismiss workers for one or both industries. Therefore, the law of motion for firm's labor evolution is given by,

$$\theta_i' n_i' + (1-\theta_i')n_i' = (\theta_i n_i + (1-\theta_i)n_i) + (e_{1i} + e_{2i}) \tag{2.13}$$

$$n_i' = n_i + (e_{1i} + e_{2i}) \tag{2.14}$$

where e_{1i}, e_{2i} are the labor adjusted in the current period. Firm i however, incurs costs when it dismisses workers. These costs are due to the enforcement and implementation of job destruction policies within this economy. I evaluate the effect of two types of job destruction policies on firm and aggregate variables,

1. Similar to Hopenhayn and Rogerson (1993), firms have to pay linear redundancy costs which are are size independent when dismissing workers. Also, I assume that firms within the group are independent and dismissal costs have to be paid by each of them. Total group adjustment costs are given as,

   $$G(Z_i, n_i, \theta_i, n_i', \theta_i') = \tau max\{\theta_i n_i - \theta_i' n_i', 0\} + \tau max\{(1-\theta_i)n_i - (1-\theta_i')n_i'\} \tag{2.15}$$

   In principle, firms also incur search and training costs while hiring workers. However, I focus only on job destruction policies so as to isolate its effect in a model in which firm diversification is endogenous. Additionally, this model outline is also consistent with the empirical evidence that I furnished in the previous sections.

   Under these non-convex adjustment costs, Samuel Bentolila (1990) shows that the optimal labor accumulation policy follows a (s,S) rule. When the gains from adjusting labor are low for firms, then the firm remains inactive. Firms only adjust when the gains are high (firm's labor stock is much larger or much smaller than the efficient level).

2. I also formulate job destruction policies to be size-dependent. I do this as these types of policies seem to be quite prevalent in several developing countries like India, Indonesia, Chile and others. I assume that firms with labor levels greater than a cutoff level $\bar{N}$ bear higher redundancy costs given by the tax τ_h. Whereas, firms with labor levels less that $\bar{N}$ bear lower (or zero) redundancy costs given by τ_l. Here, $\tau_h > \tau_l$ and again these dismissal

costs are incurred by each firm belonging to the group,

$$G(Z_i, n_i, \theta_i, n_i', \theta_i') = \tau_h max\{\theta_i n_i - \theta_i' n_i', 0\}\mathbb{I}_{\theta_i n_i \geq \bar{N}} + \tau_l max\{n_i - n_i', 0\}\mathbb{I}_{\theta_i n_i < \bar{N}} \quad (2.16)$$

$$+\tau_h max\{(1-\theta_i)n_i - (1-\theta_i')n_i', 0\}\mathbb{I}_{(1-\theta_i)n_i \geq \bar{N}} + \tau_l max\{(1-\theta_i)n_i - (1-\theta_i')n_i', 0\}\mathbb{I}_{(1-\theta_i)n_i < \bar{N}}$$

2.4.4 Aggregate Stationary Competitive Equilibrium

In the benchmark specification, there is only idiosyncratic uncertainty in the model. I solve for the model's stationary equilibrium in which all aggregate variables are constant and the distribution of firms over the productivity-labor-organizational form space does not change.

Dynamic problem of the firm

Each firm takes the aggregate wage W as given. The dynamic programming problem for firm i with accumulated labor n_i, fraction θ_i allocated to industry 1 and industrial productivity shocks $Z_i = (Z_{1i}, Z_{2i})$ is given by the following Bellman equation,

$$V(Z_i, n_i, \theta_i; W) = \max_{\theta_i', n_i'} \left[d_i + \frac{1}{1+r} \int V(Z_i', n_i', \theta_i'; W) dP(Z_i'|Z_i) \right] \quad (2.17)$$

where firm dividends are industrial profits net of adjustment costs,

$$d_i = \pi(Z_{1i}, n_i, \theta_i; W) + \pi(Z_{2i}, n_i, 1-\theta_i; W) - G(Z_i, n_i, \theta_i, n_i', \theta_i') \quad (2.18)$$

evolution of labor accumulation is,

$$n_i' = (1-\delta_s)n_i + e_{1i} + e_{2i} \quad (2.19)$$

and firm organizational choices for the next period are,

$$\theta_i' \in \begin{cases} \{1\} \cup (0,1) & \text{if } \theta_i = 1 \\ \{0\} \cup (0,1) & \text{if } \theta_i = 0 \\ \{0\} \cup \{1\} \cup (0,1) & \text{if } \theta_i \in (0,1) \end{cases} \quad (2.20)$$

Let the policy functions associated with labor and industrial allocation decisions of firms be given by, $N(Z, n, \theta; W)$ and $\Theta(Z, n, \theta; W)$. These policy functions are obtained after solving the above Bellman equation.

Stationary Firm Distribution

At time t, the state of each firm is completely described by the tuple (Z, n, θ) and therefore, the state of both industries is completely described by the distribution of firms over this four-dimensional state. Let all firms in the beginning of the period be represented by the measure $\mu(Z, n, \theta)$. In the numerical computation of this problem, each of these state variables take a finite set of values. Therefore, the measure μ can be represented as a matrix with each element (i, j, k, m) of this matrix equal to the total mass of firms with individual state $(Z_{1i}, Z_{2j}, n_k, \theta_m)$.

Then, the law of motion of this distribution is given as,

$$\mu(Z', n', \theta') = \int \mathbb{I}_{n'=N(Z,n,\theta;W)} \mathbb{I}_{\theta'=\Theta(Z,n,\theta;W)} dP(Z'|Z) d\mu(Z, n, \theta) \tag{2.21}$$

where $\mathbb{I}$ is the indicator function. The above equation says that the new measure of firms, μ', evolves so that firm productivity shocks are exogenously received in period $t+1$ but labor and industry allocation decisions are optimally determined by all firms in the previous period. In every period, the total mass of firms stays constant as I do not consider the entry-exit margin within the above model. In a stationary distribution, we should get the cross-sectional firm distribution to remain constant i.e. $\mu' = \mu$.

Household sector

The economy is populated by a continuum of households. Each household derives utility from consumption and leisure and its preferences are defined as,

$$\sum_{t=0}^{\infty} \left[\beta^t [u(C_t) + v(L_t) \right] \tag{2.22}$$

where C_t is household's consumption and N_t is households labor for period t.

In this economy, the household has a limited role to play. It does not accumulate financing assets, earns income, consumes and supplies labor. There is also no aggregate uncertainty in the model, all aggregate quantities and prices are constant. Therefore, the problem of the household reduces to a static problem which is optimized according to,

$$max_{C,L} \left[log(C - AL) \right] \tag{2.23}$$

subject to its budget constraint,

$$C = WL + D + \Psi \tag{2.24}$$

The household earns income from supplying labor, earns dividends from the stationary measure of firms and earns redundancy payments from labor-firing decisions of firms. Solution of this static problem yields a final demand for all goods produced in the economy given by $C^d = C(\mu; W, D, \Psi)$ and an infinitely elastic supply of labor when $W = A$. This condition exogenously pins down the wage rate where A denotes the labor participation rate in the stationary economy.

Equilibrium Definition 1. *A stationary, competitive equilibrium in this economy is:*
(i) defined by a set of optimal policy functions $N(.)$, $\Theta(.)$, $d(.)$, $G(.)$ and value functions $V(.)$ for every firm;
(ii) an optimal consumption function for the household given by $C^d(.)$;

(iii) an equilibrium wage rate W; and
(iv) a stationary measure μ of firms such that,

$$C^d(\mu, W) = W\int N(s;W)\mu(ds) + \int d(s, N(s;W), \Theta(s;W))\mu(ds) + \int G(s, N(s;W), \Theta(s;W))\mu(ds) \tag{2.25}$$

and

$$\mu' = \mu \tag{2.26}$$

where $s = (Z, n, \theta)$ are state variables for each firm.

In the above definition, the stationary competitive equilibrium is such that all firms optimize by taking their individual state and aggregate wage as given. This firm-level optimization problem generates their labor accumulation, industry allocation, dividends and adjustment cost functions which are described by Condition (i). In the aggregate, all markets clear i.e. the aggregate goods and labor market clears and the cross-sectional firm distribution does not change over time. This is represented by Conditions (ii), (iii) and (iv).

The existence of a stationary competitive equilibrium in the above problem is easy to obtain. By assuming that household preferences are given by $log(C - AL)$, I get the result that households will supply any amount of labor at price $A = W$. This trivially generates equilibrium in the aggregate goods and labor markets. Therefore, after solving the model I obtain a non-degenerate, cross-sectional distribution of firms μ in which firms are differentially sized and have different organizational structures. In the long-run equilibrium, we can assess the effects of different job destruction policies both at the micro firm-level and at the aggregate economy level.

2.5 Calibration of Benchmark Model

In the stationary equilibrium and at the individual firm-level we see that, some firms expand whereas others contract based on the productivity shocks that they receive in both industries. Their labor accumulation and de-accumulation decisions are optimally determined according to the policy functions. However, the aggregate variables and prices are constant.

Before performing the quantitative analysis, I need to specify or estimate parameter values which result in the model approximately representing the actual economy across certain dimensions. To do this, I follow the procedure used in Hopenhayn and Rogerson (1993) and Moscoso Boedo (2012) and calibrate the benchmark model economy. I assume that the benchmark version of model is one in which firms face zero firing costs and it generates moments that are matched to moments computed from US establishment level-data. The above assumption implies that the US economy closely approximates the frictionless, benchmark model economy where firms face zero firing costs and this is consistent with actual firing costs data as estimated by the *Doing Business Database*.

Known parameters

As is standard in the real business-cycle literature, α_l is equal to the labor share of income and is assigned a value of 0.64. The discount factor β is equal to 0.94 which implies a real interest rate of 6%. Similar to Gomes and Livdan (2004), the cost of labor W gets determined automatically by considering household preferences of the form 2.23 and by setting the marginal dis-utility parameter A equal to 0.5.

Unknown parameter identification

Firstly, I specify the two industrial productivity shocks to be independent of each other which implies that the variance-covariance matrix can be reduced to,

$$\Sigma = \begin{bmatrix} \sigma_z^2 & 0 \\ 0 & \sigma_z^2 \end{bmatrix}$$

The remaining parameters of the model are unknown and their values can be obtained by calibrating the model to US firm-level data. These parameters are $(\mu_z, \rho_z, \sigma_z, f)$ which are the long-run mean, persistence and standard deviation of the industrial productivity shocks and the fixed operating costs that firms have to pay for production purposes. I now explain what moments enable identifiation of the above parameters.

Firstly, a higher mean μ_z increases the average size of firms in the economy. Since, firms can attain larger sizes in this economy, they are also more likely to diversify as their growth options reduce within their incumbent industry. Therefore, μ_z also positively affects the proportion of group firms in the economy. The persistence parameter ρ_z directly affects the persistence of firm (log) employment levels. As productivity shocks become more persistent, firms will deviate less from their optimal employment targets and their labor adjustment process will be less frequent. Therefore, the autocorrelation of (log) employment levels identifies ρ_z. σ_z increases the volatility of firm productivity shocks. If shocks are more volatile and persistent, then firms will respond to a high productivity shock by creating more jobs and respond to a low productivity shock by destroying more jobs. The standard deviation in (log) employment growth rate will also increase with σ_z.

Finally, fixed cost f is determined by matching the proportion of business-group firms/conglomerate-establishments within the US economy. As specified in the model, firms have to pay double the fixed costs if they choose to diversify and produce goods of both industries. If these fixed costs are too low then all firms will choose to diversify and a zero measure of stand-alone firms will arise in equilibrium. Else, if the fixed costs are too high then none of the firms will diversify and will focus their production activities within a single industry.

2.5.1 Model Solution Algorithm

The benchmark model cannot be solved analytically and therefore, is numerically solved using the principles of dynamic programming. I first solve for firm's value function and its optimal policy functions. Each firm's value function V_i and associated policy functions (θ_i', n_i') are functions of four state variables: the two industry productivity shocks (Z_{1i}, Z_{2i}), the fraction of labor allocated to industry 1 θ_i and the total labor stock of the firm n_i. I discretize this four-dimensional state space so that industry labor accumulation functions can be chosen by firms for the next-period $(\theta_i' n_i', (1-\theta_i)n_i)$, I discretize the four-dimensional state space.

Since, I assume that $log(Z_{1i})$ and $log(Z_{2i})$ follow AR(1) processes with mean μ_z, persistence ρ_z and variance of the idiosyncratic shock σ_z^2. The shock processes are discretized using Rouwenhorst (1995) quadrature-based method which is considered to be more reliable for approximating highly persistent processes. I assume that the state space of each productivity shock consists of $nz = 12$ points. Firms can choose their total labor level from a grid consisting of $nl = 150$ points. A log-scale is used for firms employment stock and I assume that the maximum number of employees that a firm can have is 300 workers. The proportion of employees allocated to industry 1 can take any value between the set $[0, 1]$ and this interval is discretized into $nt = 10$ equally spaced points. Therefore, Firm i's optimal value function and policy functions will be of dimension $(nz = 12, nz = 12, nl = 150, nt = 10)$. Typically, we want a finer grid that firm i can choose from when making its next period labor and industry allocation decisions. Therefore, I expand the next-period labor choice space to $nl_1 = 180$ points and next period allocation space to $nt_1 = 11$.

After solving for the value function $V(Z, n, \theta)$ and policy functions $N(Z, n, \theta)$ and $\Theta(Z, n, \theta)$, I simulate a series of industrial productivity shocks for N firms for T time periods. This generates a series $\{(Z_{1it}, Z_{2it})\}$ for all firms i and for all time periods t. I assume that in the initial period, all firms start with the steady state level of labor l_{ss} and they are uniformly assigned to either industry 1 or industry 2. Therefore, I am assuming that each firm starts off as a stand-alone firm which we should expect to hold in the real world as well. Now, for every other peiod I compute the firms industrial labor accumulation decisions by using their simulated productivity shocks and the optimal policy functions that are computed before.

The above procedure generates a distribution of firms in every period, $\mu(Z_i, n_i, \theta_i)$ and using the law of motion 2.21, we get the next-period's cross-sectional firm distribution, $\mu'(Z_i', n_i', \theta_i')$. I iterate over these distributions till the distance between them becomes very small.[17]

2.5.2 Data Sources and Model Calibration

I calibrate the model to US-establishment level data. In Table **??**, I report the empirical data moments and the matched model moments which are used for calibrating the unknown parameters. In Table 2.5, I report the specified and calibrated parameter values that are obtained for the benchmark model. The moments from US establishment-level data are computed from the Statistics of U.S. Businesses (SUSB) 2002-2004 dataset and I use the values as reported in Moscoso Boedo (2012). The average size of US establishments in the data is 17.6 which is quite close to the average size that I get 16.06. This is obtained by setting mean productivity level $\mu_z = 0.025$. Davis and Haltiwanger (1992) and Hopenhayn and Rogerson (1993) document that employment tends to be quite persistent. I target an employment serial correlation of 0.93

[17] Like the procedure used by Krusell and Smith (2006), I approximate the cross-sectional distrubution by computing the aggregate labor employed by all firms $log(L)$. The forecasting rule for next period's aggregate labor is then specified as $log(L') = a + blog(L) + \epsilon$. The steady state cross-sectional distribution is one in which the estimated parameters a and b of the forecasting rule do not change.

Table 2.4: Calibration of Benchmark Model without job protection policies

Calibration: Empirical data and model moments		
	Data	Model
Average firm size (employment)	17.60	16.06
Serial correlation in (log) employment	0.93	0.92
St. deviation in employment growth rates	0.30	0.28
Total Job creation rate (%)	15.8	9.07
Total Job destruction rate (%)	14.4	8.55
Prop of business-group firms	0.60	0.60

Table 2.5: Parameter values: Calibration of benchmark model without job protection policies

Exogenous and calibrated parameter values		
Exogenous parameters		
Labor share of income	α_l	0.64
Discount factor	β	0.94
Marginal dis-utility parameter (Wage)	$A(W)$	0.5
Calibrated parameters		
Mean productivity level	μ_z	0.025
Serial correlation of productivity shocks	ρ_z	0.95
Standard deviation of productivity shocks	σ_z	0.11
Prop of diversified group-firms	f	1.70

which implies a large value of persistence for the productivity shock $\rho_z = 0.95$. To determine how volatile industrial productivity shocks are, I try and match several dispersion measures: standard deviation in employment growth rate, average job creation and job destrution rate. In the data, the job creation and job destruction rates are quite high at 15.8 and 14.4 respectively. Whereas using the model, a significantly lower amount of job creations and job destructions are generated (8-9%). Since, I do not include firm entry and exit within the model, I cannot take into account the reallocation process which arises due to firm creation and destruction. Therefore, the model will not be able to accurately match the job creation/destruction rates. I then use the standard deviation in employment growth rates as the principle moment to be matched. Davis, Haltiwanger, Jarmin, and Miranda (2006) report a range of values for this parameter 0.22-0.30. I match the upper limit of this interval and the calibrated value of σ_z that I obtain is 0.11. Finally, Gomes and Livdan (2004) use a statistic of 0.60 as the proportion of diversified group-firms within the US economy and this generates fixed operating costs of $f = 1.7$ through the model.

Model implied firm size distribution

Table 2.6: Firm size distribution (in percent) in benchmark model without job protection policies

	Data	Benchmark model		
	All firms	All firms	Stand-alone firms	Bus.-group firms
No of employees				
[1-4]	48.52	5.85	12.61	1.30
[5-9]	21.52	26.92	21.82	30.35
[10-19]	14.24	38.79	21.61	50.33
[20-49]	9.77	11.38	13.59	9.90
[50-99]	3.32	3.64	2.30	4.55
100+	2.61	0.71	0.99	0.53

Table 2.6 describes the firm size distribution of all firms, stand-alone firms and business-group firms using the calibrated benchmark model that does not consider any job protection policies. We see that majority of the firms employ 5-19 workers. Only 6% of the firms lie in the smallest size category (0-4 workers) whereas a much smaller 4.35% proportion of the firms employ more than 50 workers. We also see that stand-alone firms are typically smaller than the average firm and business-group firms are typically larger. While 5.08% of business-group firms employ more than 50 workers, this proportion is smaller at 3.3% for stand-alone firms.

If we this distribution of firm sizes with the actual distribution based on US establishment level data, we find that the fit isn't very accurate. Namely, the model generates a much smaller proportion of firms in the smallest size categories (0-4 workers) and a much larger proportion in the medium size categories (10-49 workers). Based on the statistics as presented in Moscoso Boedo (2012), about 50% of all firms in the data employ 0-4 workers whereas the model generates only 6% of all firms. This discrepancy is due to the firm entry and exit margin not being included in the benchmark model. Future revisions of the model would include these margins so as to generate a better fit with respect to firm size distribution, job creation and job destruction rates.

2.5.3 Decision to diversify

In Figures 2.4(a) and 2.4(b), I plot a stand-alone firm's decision to diversify as a function of the idiosyncratic productivity shocks that it receives in industries 1 and 2 and its size. Here, the dependent variable is the unconditional probability that a stand-alone firm diversifies and it is obtained using the stationary distribution of stand-alone firms in the benchmark model.

Based on Figure 2.4(a), we see that the probability to diversify is largest for stand-alone firms when they have low growth options in their current industry and relatively higher growth options in industry 2 i.e. low Z_{1i} and relatively higher Z_{2i}. This region is displayed using the red color scheme. Alternatively, the probability to diversify is smallest for stand-alone firms when the opportunity costs of diversifying are large i.e. their productivity is much higher in their current industry 1 (high Z_{1i} and relatively lower Z_{2i}). Therefore, like Gomes and Livdan (2004), I obtain the result that diversification arises due to optimal decision making and it depends on the underlying comparative advantage of stand-alone firms in both industries.

Productivity shocks are not the only factors that determine firm diversification. In Figure 2.4(b), I plot the relation between the unconditional probability of diversifying and firm size which is measured using the (log) number of firm employees. We see a clear, non-linear but increasing relationship between these two variables suggesting that larger firms are more likely to diversify. This result arises due to the assumption of a decreasing returns to scale production function which implies limited growth options for firms within any industry. Conditional on a given tuple of productivity shocks, as firms become larger, their growth options reduce and the benefits of diversification increase. In the model, increases in firm scale and scope are optimal and do not arise due to suboptimal empire building decisions of managers.

2.6 Counterfactual Analysis with Job protection policies

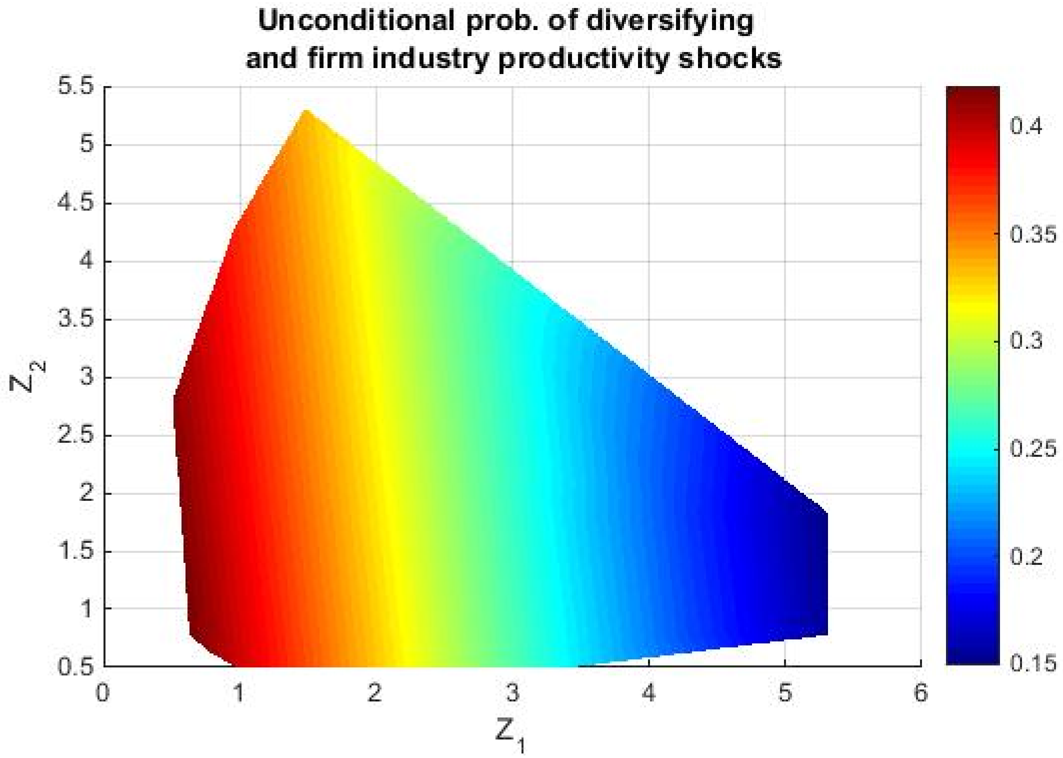
2.6.1 Cross-sectional and aggregate implications of Job destruction policies

This section displays the results of our counterfactual experiments in which I alter the values of firing costs that firms incur when they reduce their previous employment levels. In these experiments, job destruction taxes can either be size independent or size dependent. That is these taxes can either apply uniformly across all firm types or they can be more severe for larger firms instead of smaller firms. Like Hopenhayn and Rogerson (1993), I use the model to compute the effect of job destruction taxes, $\tau = W$, which implies that all firms have to pay workers their annual salary at the time of dismissal. For size-dependent policies, consistent with the actual evidence from Sri Lanka and Europe, I consider the effect of job destruction taxes, $\tau_h = W, \tau_l = 0$, which implies that only firms with more than 15 workers ($N >= \bar{N} = 15$) have to pay workers their annual salary at the time of dismissal.

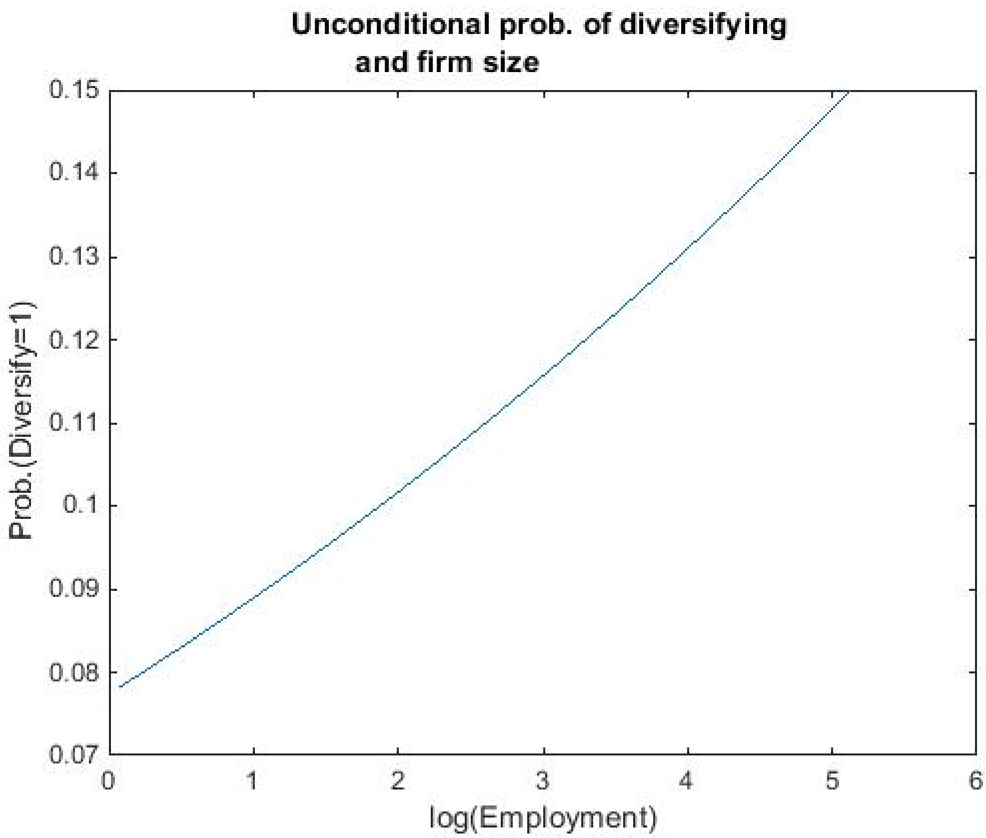
Table 2.7 summarizes the results of these taxes on various cross-sectional and aggregate statistics. Firstly, we see that when taxes are size-dependent then the average firm size falls from 16.06 workers to 15.05 workers. With size-independent taxes, the average firm size slightly increases to 16.7 workers. Contrary to the results that Hopenhayn and Rogerson (1993) and Moscoso Boedo (2012) obtain, I find that firm employment becomes more volatile, slightly less persistent with job destruction taxes. The job creation and job destruction rates increase from 9% to 11% and the serial correlation of log employment reduces slightly from 0.92 to 0.91 when $\tau = W$. We also see that under these experiments, firms find it more costly to increase their aggregate labor stock and this results in the proportion of diversified-group firms decreasing from 0.60 to 0.44.

As far as aggregate statistics are concerned, we find that job destruction policies have significant aggregate implications with the effects on aggregate labor demand much larger than the effects on aggregate ouput/productivity. Also, consistent with intuition when taxes apply uniformly across all firms, then the effects on aggregate variables are more severe as compared to the results obtained from the model with size-dependent taxes.[18] As displayed in Table 2.7, aggregate output drops by about 4% when taxes are dependent on the size of the firm and the

[18] It will be interesting to determine if these results continue to hold if the entry/exit margin is also included and/or if aggregate prices are also determined through the model. For simplicity, in the above models, I do not allow for firm entry-firm exit and the aggregate wage is exogenously determined outside the model.



(a)



(b)

Figure 2.3: Determinants of Decision to diversify

Table 2.7: Cross-sectional and Aggregate effects of size-dependent and size-independent job destruction policies

	Benchmark Model $\tau, \tau_h = 0$	Model with $\tau_h = W, \bar{N} = 15$	Model with $\tau = W$
Average firm size (employment)	16.06	15.21	16.69
Serial correlation in (log) employment	0.92	0.91	0.90
St. deviation in employment growth rates	0.28	0.30	0.31
Total Job creation rate %	9.07	9.92	11.02
Total Job destruction rate %	8.55	9.47	11.67
Prop. of group firms	0.60	0.60	0.44
Aggregate Statistics			
Aggregate Output	1.00	0.96	0.95
Aggregate Labor	1.00	0.95	0.93
Aggregate TFP	1.00	0.99	0.99

drop is slightly larger at 6% when all firms have to pay these taxes. If we look at the statistics for the aggregate labor demand (supply), then we see that demand reduces significantly by 7% when $\tau = W$ and it reduces by 5% when taxes only have to paid by firms with more than 15 workers. Finally, the effects on aggregate productivity are not very significant i.e. I find that (relative) aggregate productivity only decreases by 1% when taxes are positive.

2.6.2 Deviations in the marginal revenue product of labor with Job destruction policies

In Table 2.8, I represent various statistics on labor misallocation measures. Here, labor misallocation is represented by the dispersion in the marginal revenue product of labor. If we consider a static model of firm production with firms producing their differentiated goods using the Cobb-Douglas production function and if we assume that labor markets are frictionless then we get the result that the marginal revenue product of labor should be equal across all firms i.e. cross-sectional dispersion measures should be equal to zero.

Using the model, we get the result that the steady-state cross-sectional dispersion in $log(R/L)$ is not equal to zero even in the benchmark model. I get this result as labor is a dynamic input for firms and labor misallocation would arise even in the absence of distortionary policies due to volatile productivity shocks. Therefore, dispersion is 0.11 in the benchmark model and it increases to 0.12 and 0.13 when taxes are introduced into the model. We also see that when taxes are positive, the proportion of firms with large deviations in $log(R/L)$ from the aggregate wage level W also increases. In the benchmark model, only 1% of the firms display deviations of more than 20% however, when we include job destruction policies then this proportion increases to 7%. The proportion of firms with small deviations from the aggregate wage decreases from 77% in the benchmark model to 69% in the model with $\tau = W$.

Table 2.8: Effects of size-dependent and size-independent job destruction policies on Labor misallocation measures

	Benchmark Model $\tau, \tau_h = 0$	Model with $\tau_h = W, \bar{N} = 15$	Model with $\tau = W$
St. deviation in log(R/L)			
All firms	0.1142	0.1197	0.1278
Stand-alone firms			
Business-group firms			
Absolution deviation of log(R/L) from W			
(0-5 %]	0.77	0.73	0.69
(5-10 %]	0.12	0.14	0.19
(10-15 %]	0.09	0.09	0.09
(15-20 %]	0.01	0.03	0.02
More than 20 %	0.01	0.01	0.07

2.6.3 Cross-sectional and aggregate effect of job destruction policies if diversification is not allowed

In this exercise I determine what will be the implications of these size-dependent and size-independent job destruction policies if firms are not allowed to form business groups. If we find that job destruction policies generate larger aggregate losses when firms are not allowed to diversify then this would imply that diversification as a firm organizational strategy alleviates some of the effects of these policies. In a single industry model, we know that firms becomes more cautious about changing their employment levels when they face firing costs. Compared to the frictionless situation, firms are reluctant to reduce their employment levels when they receive a lower than expected productivity shock as the marginal costs of firing workers increases. Firms are also reluctant to increase their employment levels when they receive a higher than expected productivity shock as the future marginal benefits are lower. (As productivity shocks are uncertain, firms may not want to increase their current employment levels if they estimate that they would receive a low productivity shock in the future and then they would have to pay higher firing costs.)

With firm diversification, business-group firms have higher organizational flexibility as they can reallocate their excess labor across both their industries. This makes them less cautious about hiring and firing workers in the current period and can thus alleviate atleast some of the effects of these distortionary job destruction policies. In Table, I present the effects of job-destruction policies on various aggregate and cross-sectional variables in a model in which firms are not allowed to diversify and size-dependent/size-independent job destruction policies are introduced.

2.7 Conclusion

Chapter 3

Commitment Through Borrowing

3.1 Introduction

People are known to have self-control issues; their bias for immediate gratification can result in deviations from their long-term goals/plans[1]. Self-control issues can be especially binding for the poor. For instance, recent experimental evidence finds that the poor do not invest in high-return projects, they demand commitment devices like lock-boxes and commitment saving products, they borrow small amounts at very high interest rates. These observations tell us that the poor may have a bias for present consumption which can lead them to deviate from their long-term objectives. Poverty can also perpetuate itself under this lack of self-control. Banerjee and Duflo (2011), Banerjee and Mullainathan (2010), Bernheim, Ray, and Yeltekin (2015) argue that sufficiently poor people with self-control issues may not save enough as they expect their future selves to overconsume and this can lead to a poverty trap.

The lack of self-control by the poor also has important implications for the promotion of micro-finance and micro-credit. In the past couple of decades, the micro-finance industry has seen tremendous growth. The size of the micro-finance industry is approximately 60-100 billion dollars and it serves about 200 million clients worldwide (Banerjee and Duflo (2011)). A large variety of institutions operate in this market and offer diverse financial products and services to low income households. Some of these institutions include NGOs (non-governmental organizations), cooperatives, credit unions and for-profit Micro-finance institutions (MFIs)[2]. Micro-

[1]The Strotz (1955) was the first to study and model self-control. He showed that if an individuals discount function is non-exponential then her intertemporal behavior will be dynamically inconsistent and her current and future preferences would be unequal. He emphasized that these individuals may demand commitment mechanisms to pre-commit their future behavior and stick to their initial, optimal plan. Kavka (1994) conducted experiments using animal and human subjects and showed that their discount functions are approximately hyperbolic. Hyperbolic discount functions imply that immediate future rewards are discounted to a much larger degree than distant future rewards. The golden-eggs model of Laibson (1997) introduces the quasi-hyperbolic discount structure in a consumption-savings problem and uses it to explain some empirically observed facts like the high demand for illiquid assets by the US household sector, the high sensitivity of consumption to household income. DellaVigna and Malmendier (2004), DellaVigna and Malmendier (2006) provide theoretical and empirical evidence on the types of contracts offered by profit-maximizing firms who supply investment goods/leisure goods to consumers with quasi-hyperbolic discount preferences. They find that partially naive consumers will overpay and the profit maximizing contract offered is back-loaded and consists of switching costs.

[2]Unlike the Grameen lending model, certain MFIs have profit maximization as their primary mandate not poverty alleviation. For instance, Banco Compartamos (Mexico) and SKS Microfinance (India) transitioned from NGOs to publicly-traded companies in 2007 and 2010 respectively. Banco Sol is a for-profit commercial bank operating in Bolivia

finance especially micro-credit is regarded as an important tool to eradicate global poverty.

Micro-credit is the act of making small loans to the poor. The inception of micro-credit began with the setup of the Grameen Bank by Dr. Muhammad Yunus in Bangladesh in 1976. In 2006, both Dr. Yunus and Grameen Bank were awarded the Nobel Peace Prize and were recognized for their efforts to improve the economic and social conditions of the poor through the use of micro-credit programs. Micro-credit is therefore typically meant to help low income households (especially women) initiate or expand their micro-businesses and small business activity. Prior to the advent of micro-credit, the poor could not borrow from formal financial institutions. Lending to the poor was considered risky as the poor do not have credit histories and have limited assets to pledge. Supplying small loans to the poor is financially unsustainable for banks as large fixed costs have to be incurred by them while monitoring and screening poor borrowers[3]. Given the current enthusiasm surrounding micro-credit and the vast reach of the micro-credit industry, it is important to determine whether it actually helps the poor.

In this paper, I study what kinds of credit contracts should be offered by MFIs when borrowers have time inconsistent preferences and they have a lumpy investment opportunity to finance. The model that I use consists of an entrepreneur who lives for three periods and time inconsistency arises due to her quasi-hyperbolic preferences also known as $\beta - \delta$ preferences (Laibson (1997), O'Donoghue and Rabin (1999)). In my analysis, I assume that the entrepreneur is sophisticated. She is aware of her ex-post self-control issues and can correct her behavior ex-ante through the use of external commitment devices. I determine the types of micro-credit contracts that serve as external commitment devices and prompt the entrepreneur to invest.

In the model, I consider an entrepreneur who receives labor income and has a known investment opportunity in the second period of her life. I assume that she can only finance this investment if she borrows from MFIs using a perfectly enforceable credit contract. Therefore in the absence of MFIs (under financial autarky) she cannot borrow or invest but can save if her income profile is downward sloping. If the entrepreneur has access to MFIs and if she has time inconsistent preferences then following past literature, her investment and borrowing decisions are determined via a dynamic game played between her successive incarnations or selves. In this case, her intermediate self i.e Self 2 can use the first best loan amount for consumption instead of investment. Therefore moral hazard on part of the borrower in the intermediate stage of her life can lead to sub-optimal use of the loan. I show that this result arises under two conditions. Firstly, the entrepreneur should be relatively impatient, i.e. her quasi-hyperbolic discount factor should be significantly high. Secondly, her investment project should generate moderate returns. If both of these conditions hold then, the non-investment option is more binding for Self 2 and given this behavior, the best response for Self 1 is to not issue the first best micro-credit amount.

Given this benchmark case, I then study how a MFI should design its credit contract

[3] Although some governments intervene by sponsoring targeted lending programs for the poor, these programs are largely unsuccessful and are associated with high default rates. For instance, Cole (2009) uses data from India to show that Indian state-owned banks (not private sector banks) are prone to political capture and offer more agricultural credit in election years. He then shows that this intervention is costly as default rates increase in election years and the extra credit does not improve agricultural output or investment outcomes.

so that the above problem is resolved. That is I solve for the welfare maximizing incentive compatible contract when the entrepreneur is relatively impatient but sophisticated. I show that the second-best contract features a larger loan size and more impatient borrowers are allocated larger loan sizes. By over-borrowing from the non-profit MFI, the attractiveness of the non-investment option for Self 2 reduces and this disciplines her investment/consumption decisions.

This paper is related to the literature that evaluates the impact of micro-credit on the livelihoods of the poor. Empirically, we see that micro-credit is associated with certain rigid features. The loan size offered is small and fixed; the loan repayment frequency is high (often weekly or monthly repayments have to be made immediately after the loan is disbursed); loans are generally made to groups of borrowers and the entire group is jointly liable for repayment. This rigidity can reduce the attractiveness of micro-credit for borrowers and reduce the take-up rate. Recently a number of randomized control experiments have been executed by economic researchers to determine the effectiveness of micro-credit and its various features on the livelihoods and consumption/investment decision making of the poor. Banerjee, Duflo, Glennerster, and Kinnan (2015) perform a controlled experiment in which micro-credit is offered through a large Indian MFI to slums in Hyderabad, India. Prior to this intervention, majority of the households in these slums did not have access to formal finance and borrowed from informal sources (like moneylenders, family, friends). One and half years after the intervention, they find that the take-up rate for micro-credit is a little higher (27 percent) for treatment households versus 18.3 percent for control households. While treatment households increase their business assets, there is no significant positive effect on their income/expenditure. This suggests that the poor may not have a high demand for micro-credit and the positive effect of micro-credit on business activity/household finances may not be significant. Crepon, Devoto, Duflo, and Pariente (2015) presents results from a randomized evaluation of micro-credit in rural areas of Mexico. Following the program, they find that the take-up rate for micro-credit is only 17 percent for treatment households and 0 percent for controlled households.

Traditional economic theory has been unable to explain individual behavior like procrastination, the use of commitment devices such as membership in saving clubs, investment in illiquid assets, creation of binding deadlines and goals to enhance self-control. In the Discounted utility framework as introduced by Samuelson (1938), decisions concerning intertemporal choices are made at the initial time along with the presumption that these decisions continue to be optimal at all future periods and no deviations from this plan needs to be considered. In the above scenario, the intertemporal discount factor is constant across time and the agents are exponential discounters. By allowing for present biased and time inconsistent preferences on the agent's side, a whole new field has emerged. This field has questioned the original tenets of neo-classical economics and has given way to a plethora of new research with very different implications for understanding market interactions, policy making. Moreover, there exists a sufficient amount of experimental evidence that find the discount factor to be varying and decreasing over time, i.e. people are less concerned about benefits they receive far off in future but more concerned about the immediate ones (Thaler (1981), Thaler and Shefrin (1981), Kavka (1994), Frederick, Loewenstein, and O'Donoghue (2002)). In other words, the discount factor is a hyperbolic function of time. Hyperbolic discount preferences can be approximately represented by the $\beta - \delta$ preferences (Laibson (1997), O'Donoghue and Rabin (1999)) with β being the usual exponential discount factor of the agent and $0 < \delta < 1$ being the hyperbolic component. This is also termed as the Quasi-hyperbolic discount structure with discrete discount factors at any point in time for the future given by $\{1, \delta\beta, \delta\beta^2, \delta\beta^3, ...\}$. Under these preferences an individual is said to be composed of a far sighted planner at time 0 and myopic selves at every period t who make decisions which is in direct contrast with the optimal plan of the planner. The myopic self values immediate utility more than the utility obtained in future periods and hence, a conflict arises between decision making of the two. A sophisticated agent realizes his/her self-control problem and either uses external commitment devices or personal rules so as to modify the preferences or constrain the choice set available to the doer. In the absence of commitment, the planner and selves strategically interact with each other in a finite-horizon dynamic game with the equilibrium obtained by backward induction and it being Sub-game perfect.

The layout of the paper is as follows. The theoretical model used for the analysis is described in Section 2. In Section 3 the decision making of the entrepreneur is specified under financial autarky and when she can borrow from a non-profit MFI. Finally, in Section 5 I relate the model results to recent experimental evidence and conclude by discussing some policy implications.

3.2 Model Outline

An entrepreneur lives for three periods $i = \{1, 2, 3\}$. In period 1, the entrepreneur does not consume but just makes borrowing/saving decisions for her future. In period 2, she consumes and decides to invest or not in a project. This investment project is only available in period 2 and requires some fixed capital k with benefits b being generated one period later in period 3. This project is lumpy and has positive present value $b > k$[4]. To simplify the analysis I also assume that the interest rate earned on savings within this environment is zero.

The entrepreneur has some initial non-stochastic wealth w in period 1. In period 2 she does not earn anything. In period 3, she either earns the benefits b from the investment project or she earns income w' if the project cost k wasn't incurred in period 2[5].

The decision making timeline for the entrepreneur is described in Figure 3.1,

[4]The investment project here can be a durable good or an investment good which the entrepreneur decides to purchase. The other good in this setup is the consumption good which can include expenditure on basic food, health, non-essential items like temptation goods. Time consistency here arises because of the hyperbolic discounting framework and does not follow the novel approach used by Banerjee and Mullainathan (2010). They assume a different set of preferences and consider individual expenditure on two types of consumption goods: non-temptation goods versus temptation goods/sin goods. While individuals value any current expenditure on temptation goods they view any future expenditure on these goods as sub-optimal and a tax on their income, savings behavior. The authors then assume that the marginal dollar that is spent on temptation goods is a concave function of income i.e. the poor spend a larger portion of their income on temptation goods. This results in them appearing more impatient and can lead to a poverty trap.

[5]The results from the analysis would not change if I instead assumed that some income was earned in period 2. It is however, important that this income is not very large. In this case, some income (eg. labor income) is earned by the entrepreneur in both periods 1 and 2. In period 3, the entrepreneur can either invest in the project and earn its returns or become a worker by supplying her labor in the external labor market.

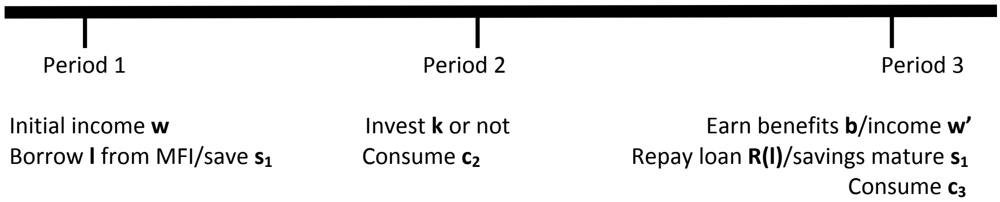


Figure 3.1: Timeline for decision making by the entrepreneur

3.3 Decision Making of sophisticated entrepreneur

Let the entrepreneurs preferences be represented by a strictly concave, increasing, twice continuously differentiable utility function $u(.)$. I assume that the entrepreneur requires some minimum consumption level c_{min} in any period and $u'(c_{min}) = \infty$.

For my analysis I will assume that the agent is a sophisticated quasi-hyperbolic discounter - she is aware that her future selves can behave in a time-inconsistent manner[6]. I implicitly assume that there is no exponential discounting, her exponential discount factor $\beta = 1$. However, her hyperbolic discount factor is denoted by δ and $0 < \delta < 1$. Following the standard practice in this literature, the agent is composed of three different selves at periods 1, 2 and 3 with Self 1 and Self 2 differing in their preference structure and decision making ability. I assume that Self 1's preferences are given as,

$$U_1(\delta; c_2, c_3) = \delta \Big[u(c_2) + u(c_3) \Big] \tag{3.1}$$

whereas, Self 2's preferences are given by,

$$U_2(\delta; c_2, c_3) = u(c_2) + \delta u(c_3) \tag{3.2}$$

3.3.1 Financial Autarky

I first characterize the optimal decisions of the entrepreneur in financial autarky i.e. when she cannot borrow from any lender. Though she cannot borrow, I assume that she can save in period 1[7].

I assume that the entrepreneur is poor and her initial wealth is insufficient to finance the cost of the investment project $w < k$. Since, the entrepreneur does not have the internal

[6]Please refer to O'Donoghue and Rabin (1999), DellaVigna and Malmendier (2004), Heidhues and Koszegi (2010) for contract design when individuals have time inconsistent preferences and are naive about their self-control problems.

[7]If I instead assumed that the entrepreneur saved in period 2 (instead of period 1) and if she were a quasi-hyperbolic discounter then her total savings would be lower. By saving one period prior to the investment/consumption decision, she can save more for the future.

funds to execute the project, she earns non-project related income w' in period 3.

In financial autarky, the entrepreneur can save in period 1 in an illiquid asset to smooth her consumption across periods. If s_1 is the amount saved in period 1 out of initial wealth w then, these savings mature in period 3. Therefore, Self 1's problem is to choose savings s_1 so that her long-term utility is maximized,

$$\max_{s_1>=0} U_1(\delta; c_2, c_3) = \max_{s_1>=0} \delta \Big[u(c_2) + u(c_3)\Big]$$

subject to,

$$c_2 = w - s_1 \tag{3.3}$$

$$c_3 = w' + s_1 \tag{3.4}$$

Lemma 2. ***(Under financial autarky):*** *The entrepreneur does not invest* $\mathbb{I} = 0$ *as wealth is insufficient. She cannot borrow but she can save.*
The optimal savings s_1 *chosen by Self 1 does not depend on* δ *and is such that,*

$$u'(w - s_1) >= u'(w' + s_1) \tag{3.5}$$

If $w > w'$*, the intertemporal Euler equation will bind and the optimal savings level will be strictly positive. Else if* $w < w'$*, optimal savings will be equal to zero.*
Given s_1 *chosen by Self 1 and for* $\delta < 1$*, the Euler equation will not bind according to Self 2's preferences,*

$$u'(w - s_1) > \delta u'(w' + s_1) \tag{3.6}$$

Proof. In Self 1's maximization problem, entrepreneurs utility in period 2 and period 3 get equal weight. If future income is expected to be less than current income ($w' < w$) then, Self 1 will save some positive amount s_1 in an illiquid asset to smooth lifetime consumption. In this case, we will get an interior solution and the intertemporal Euler equation will bind. If instead, the entrepreneur expects an upward sloping income profile over her lifetime then, she will not save. Since, she cannot borrow against her higher future income, her current marginal utility from consumption will be higher than her future marginal utility.

Now if the saved amount is strictly positive then will Self 2 consider it optimal? No, Self 2 values immediate consumption more and discounts future utility more than Self 1. Therefore, although Euler equation is satisfied for Self 1 for Self 2 it will be a strict inequality.

$$\frac{u'(w - s_1)}{u'(w' + s_1)} = 1 \tag{3.7}$$

but,

$$\frac{u'(w - s_1)}{u'(w' + s_1)} = 1 > \delta \tag{3.8}$$

Self 2 considers the period-1 savings as too high and will not be able to consume her desired c_2 level. Here we have not given Self 2 the option to save in period 2 but it can easily be shown that even if Self 2 could save, she would choose not to as her current marginal utility from consumption is higher than her period-3 discounted marginal utility. □

Lemma 2 tells us that in financial autarky the entrepreneur will not invest. However, a sophisticated entrepreneur can improve her saving behavior and smooth her lifetime consumption by saving in the initial period.

3.3.2 Commitment via overborrowing

In the previous section I showed that under financial autarky, the entrepreneur cannot invest as she is financially constrained. I now consider the case when the entrepreneur is allowed to borrow against the future benefits that she realizes from her project. I first determine how much is borrowed when there is no time-inconsistency. I then establish how time-inconsistent preferences ($\delta < 1$) affect investment and borrowing decisions of the sophisticated entrepreneur.

I assume that contractual frictions like monitoring costs, information asymmetries make borrowing funds costly in this world. Although I do not explicitly model these financial frictions, I assume that they show up as a higher interest rate on borrowing. In period 1, the entrepreneur can borrow funds from a non-profit MFI which provides funds elastically at the gross interest rate of $1 + r_b$ where $r_b > 0$. If l is the amount that is borrowed in period 1, then the entrepreneur has to repay $(1 + r_b)l$ in period 3. Therefore, l is a long-term loan that Self 1 commits to from the non-profit MFI and r_b is the long-term interest rate on this loan. I assume that the debt contract is completely enforceable by the MFI and the entrepreneur cannot default in period 3[8].

In the model, there are two uses of the microcredit obtained from the MFI. It helps in financing the cost of the lumpy investment project and it smoothes consumption across periods. Also, it is important to note that the entrepreneur has positive demand for microcredit only if the borrowing interest rate is not very high. The interest rate on loans cannot be higher than the returns from the investment project which is given by $b > (1 + r_b)(k - w_2)$. This condition also gives us an upper bound on the borrowing interest rate.

Problem definition

Although the credit amount l is decided in advance by Self 1, its use is decided by Self 2. Self 2 can either use l to finance the cost of the lumpy investment project or can divert it for consumption purposes. Therefore, Self 1's problem is to choose l given the investment, consumption decisions chosen by Self 2. This is represented by the following problem,

$$\max_{l>=0} U_1(\delta; c_2(l), c_3(l)) = \max_{l>=0} \delta \Big[u(c_2(l,\delta)) + u(c_2(l,\delta)) \Big] \tag{3.9}$$

subject to budget constraints of both periods,

$$c_2(l,\delta) = w + l - k\mathbb{I}(l,\delta) \tag{3.10}$$

[8]Implicitly I am assuming that if entrepreneurs default, they incur a large punishment cost from the MFI which is much larger than the project benefits. This cost can either be a large monetary cost that the defaulting borrower has to pay or it could be a reputational cost which makes credit default suboptimal. Given this high cost, entrepreneurs prefer repaying the loan to their MFI.

$$c_3(l,\delta) = w' - (1+r_b)l + (b-w')\mathbb{I}(l,\delta) \tag{3.11}$$

where $\Big\{(c_2(l,\delta), c_3(l,\delta)), \mathbb{I}(l,\delta)\Big\}$ is the solution to Self 2's optimization problem and denotes the consumption policy and investment policy.

Self 2 takes loan l as given and chooses how much to consume, (c_2, c_3), and the investment indicator function $\mathbb{I}$ which takes the value 1 if Self 2 chooses to invest and takes the value 0 if Self 2 does not invest.

$$\max_{c_2,c_3,\mathbb{I}} U_2(\delta; c_2, c_3) = \max_{c_2,c_3,\mathbb{I}} \Big[u(c_2) + \delta u(c_3)\Big] \tag{3.12}$$

subject to budget constraints of both periods,

$$c_2 = w + l - k\mathbb{I} \tag{3.13}$$

$$c_3 = w' - (1+r_b)l + (b-w')\mathbb{I} \tag{3.14}$$

Benchmark case - Time consistent preferences

Before, I proceed to solving the decisions of Self 1 and Self 2 for an entrepreneur who has time inconsistent preferences, I first assume that the hyperbolic discount factor $\delta = 1$ and solve for the first-best borrowing, investment and consumption decisions of the entrepreneur.

Lemma 3. ***(Borrowing and time consistent preferences):*** *If the entrepreneur has time consistent preferences, $\delta = 1$, she invests provided,*

$$\frac{b}{1+r_b} - k > w'$$

The optimal amount borrowed by the entrepreneur is l^*, her consumption, investment decisions are $\{c_2(l^*,\delta), c_3(l^*,\delta), \mathbb{I}(l^*,\delta) = 1\}$ which satisfy the Euler equation,

$$u'(w + l^* - k) = (1+r_b)u'(b - (1+r_b)l^*)$$

Proof. If $\delta = 1$, the entrepreneur has time consistent preferences and the decision making for Self 1 and Self 2 are the same; equal weight is given to period 2 and period 3 consumption.

$$U_1(1; c_2, c_3) = U_2(1; c_2, c_3) = u(c_2) + u(c_3) \tag{3.15}$$

In order to determine whether the entrepreneur invests or not, we need to determine whether the investment project increases the total wealth of the entrepreneur. I assume that the net income earned from the project is higher than the income earned by entrepreneur in autarky i.e. higher than the income earned from supplying labor in the external labor market,

$$\frac{b}{1+r_b} - k > w' \tag{3.16}$$

Given that the entrepreneur chooses to invest, $\mathbb{I}(l,1) = 1$, she now determines how much to consume and borrow from the non-profit MFI given the interest rate on borrowing,

$$\max_{l>=0,c_2,c_3}\Bigg[u(c_2)+u(c_3)\Bigg] \tag{3.17}$$

subject to budget constraints of both periods,

$$c_2 = w + l - k \tag{3.18}$$

$$c_3 = b - (1 + r_b)l \tag{3.19}$$

Since the objective function is concave and is defined on a compact set, a solution exists. Also, the constraints are linear equalities, so the Kuhn Tucker conditions are necessary and sufficient to hold. Let $\{c_2(l^*, 1), c_3(l^*, 1), l^*\}$ be the optimal consumption bundle and the optimal microcredit issued by the entrepreneur. Then, this solution will satisfy the intertemporal Euler equation,

$$u'(c_2(l^*, 1)) = (1 + r_b)u'(c_3(l^*, 1)) \tag{3.20}$$

The solution l^* is the optimal loan size chosen by the entrepreneur so that the marginal cost of investment in period 2 is equated to the marginal benefit accruing from investment in period 3. By investing, the entrepreneur reduces her period-2 consumption possibilities set and she borrows from the MFI. The benefit from investment is the discounted payoff obtained in period 3 after the loan is repaid.

$$u'(w + l^* - k) = (1 + r_b)u'(b - (1 + r_b)l^*) \tag{3.21}$$

□

Lemma 3 tells us that borrowing increases the entrepreneurs welfare and her total wealth as she can invest in the lumpy project. This implies that utility from investing is strictly greater than utility from not investing when the entrepreneur has time consistent preferences.

$$u(w + l^* - k) + u(b - (1 + r_b)l^*) > max_l\Bigg[u(w + l) + u(w' - l\mathbb{I}_{l<0} - l(1 + r_b)\mathbb{I}_{l>0})\Bigg] \tag{3.22}$$

which further implies the following,

$$u(w + l^* - k) + u(b - (1 + r_b)l^*) > max_{l>0}\Bigg[u(w + l) + u(w' - l(1 + r_b))\Bigg] \tag{3.23}$$

and

$$u(w + l^* - k) + u(b - (1 + r_b)l^*) > max_{l<=0}\Bigg[u(w + l) + u(w' - l)\Bigg] \tag{3.24}$$

Time inconsistent preferences - welfare maximizing MFI

I now assume that the entrepreneur has a hyperbolic discount factor $\delta < 1$. However, she is sophisticated and is aware that her future selves can overturn her decisions. Specifically if Self 1 borrows l^* and Self 2's present bias is so large so that she utilizes the loan for consumption rather than investment then the entrepreneurs overall welfare falls. Therefore, the equilibrium borrowing, consumption and investment equilibrium is the result of a game played between Self 1 and Self 2 in which Self 1 takes into account Self 2's optimal response to the amount borrowed by her in period 1.

Lemma 4 describes under what condition Self 2's present bias does not affect the investment decision. That is, under what conditions Self 2 does not use the loan sub-optimally and prefers the non-investment option to the investment option.

Lemma 4. ***(Borrowing and time inconsistency has no effect):*** *If $l^* > \frac{w' - c_{min}}{1+r_b}$ then the welfare-maximizing MFI will offer the first-best loan amount (l^*, r_b) which will be accepted by Self 1 and Self 2 will choose to invest. In this case, Self 2's present-biased preferences ($\delta < 1$) will neither distort the entrepreneur's welfare nor her consumption profile.*

Proof. Lemma 4 says that if the optimal loan amount l^* is too large, i.e. net benefits from the investment project are large then Self 2 will always invest irrespective of her level of impatience. In this case by not investing, she would receive a labor income which is much smaller than the loan amount issued and smaller than her total project benefit. This would further imply that the entrepreneur would have to default as her income is insufficient to repay the loan. But, we initially assumed that credit contracts are completely enforceable by the MFI. Therefore, under this scenario we get that Self 2 derives greater utility by investing and her time inconsistency does not distort her decisions.

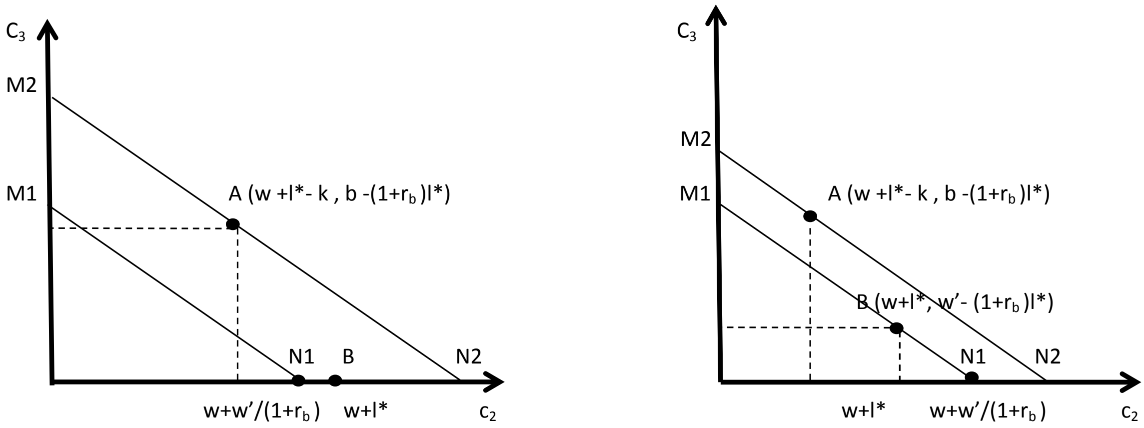
$$l^* > \frac{w' - c_{min}}{1 + r_b} \quad \Rightarrow \quad w' - l^*(1 + r_b) < c_{min} \tag{3.25}$$

The above reasoning is explained graphically using Figure 3.2. In this figure two graphs are drawn, ((a) and (b)), which represent the consumption possibilities and budget sets of the entrepreneur over her lifetime. $M1-N1$, $M2-N2$ are the budget constraints of the entrepreneur if she does not invest and if she chooses to invest respectively. We see that investment is optimal as it increases her total income. A is her first-best consumption amount when $\delta = 1$ and optimal loan amount l^* is borrowed.

In figure (a) time inconsistency is not a problem because the loan size l^* is so large that it is not affordable if Self 2 does not invest. In this case, B lies outside her autarky budget constraint and is infeasible for the borrower. In figure (b), the total project benefits and the loan size do not increase the entrepreneurs income significantly. Therefore, if her present bias is very large then Self 2 may choose to not invest and consume the entire loan amount l^* (i.e. Self 2 prefers consumption tuple B over A). $\square$

The above proposition suggests that entrepreneurial time inconsistency will only matter when the projects are mediocre that is, when they do not generate very high net returns. As the project returns are not very high, the benchmark credit amount l^* is also not very large and can be repaid from autarky period 3 income w'.

In Proposition $P4$, I consider $l^* < \frac{w' - c_{min}}{1+r_b}$ and determine how impatient does Self 2 have to be (how small does δ have to be) so that she uses the loan l^* for consumption instead of investment.



(a)

Time inconsistency not a problem
Loan l* is not affordable if do not invest

(b)

Time inconsistency might be a problem
Loan l* is affordable if do not invest

Figure 3.2: Project returns and suboptimal behavior by time inconsistent borrowers

Proposition 3. ***(Over-borrowing under time inconsistency):*** *If* $l^* < \frac{w'-c_{min}}{1+r_b}$ *and*
(i) if the entrepreneur is relatively patient $\delta \in [\hat{\delta}, 1)$*, then the welfare-maximizing MFI will offer the optimal loan amount* (l^*, r_b) *which will be accepted by Self 1 and Self 2 will invest.*
(ii) if the entrepreneur is impatient $\delta >= \hat{\delta}$*, then the welfare-maximizing MFI will offer* $l(\delta)$ *such that it satisfies the incentive compatibility constraint for Self 2. Self 1 will accept the contract, Self 2 will invest provided the contract gives more utility than the not investing option and* $b - (1 + r_b)l(\delta) >= c_{min}$*.*
(iii) the second-best loan contract $l(\delta)$ *is strictly decreasing in* δ *i.e. the more present-biased is the entrepreneur, the more Self 1 needs to over-borrow to discipline her future investment incentives.*

Proof. Given that the project returns are not very large, Self 1's problem is to borrow an amount in period 1 so that Self 2 uses the proceeds for investment. Her problem can be described by the following optimization problem,

$$\max_l U_1(\delta; c_2, c_3) = \max_l \delta \Big[u(c_2) + u(c_3) \Big] \tag{3.26}$$

subject to the budget constraints,

$$c_2 = w + l - k \tag{3.27}$$

$$c_3 = b - (1 + r_b)l \tag{3.28}$$

and the incentive compatibility constraint for Self 2,

$$u(w + l - k) + \delta u(b - (1 + r_b)l) >= u(w + l) + \delta u(w' - (1 + r_b)l) \tag{3.29}$$

(i) In the above problem, if for a certain δ the incentive compatibility constraint does not hold then, the above problem is identical to Self 1's problem under time consistency and therefore, she will borrow an amount l^* at interest rate $(1 + r_b)$ from the welfare-maximizing MFI. In this case as $\delta < 1$, Self 2's intertemporal Euler equation is not satisfied,

$$u'(w + l^* - k) > \delta(1 + r_b)u'(b - (1 + r_b)l^*) \tag{3.30}$$

Her current marginal utility from consumption is higher than her future marginal utility and if she could borrow more, she would. However, she isn't that impatient that she deviates from investing and consumes the entire loan amount. Therefore, for $\delta \in (\hat{\delta}, 1]$ the incentive compatibility constraint does not bind. Let $\delta = \hat{\delta}$ be the threshold level where the incentive compatibility constraint just binds, i.e.

$$u(w + l^* - k) + \hat{\delta} u(b - (1 + r_b)l^*) = u(w + l^*) + \hat{\delta} u(w' - (1 + r_b)l^*) \tag{3.31}$$

Also, we know that the participation constraint does not bind when loan l^* is borrowed by Self 1 as investing results in a positive income effect and the first-best consumption profile can be reached.

(ii) When $\delta > \hat{\delta}$, if Self 1 borrows l^* then Self 2 will not invest and will consume the loan. Therefore, Self 1 could borrow an amount $l(\delta)$ from the welfare-maximizing MFI which makes Self 2 indifferent between investing and not investing i.e.

$$u(w + l(\delta) - k) + \delta u(b - (1 + r_b)l(\delta)) = u(w + l(\delta)) + \delta u(w' - (1 + r_b)l(\delta)) \tag{3.32}$$

Self 1 will accept the contract provided that, her utility under investment and this larger loan size is greater than her utility under the not-investment option. That is if Self 2's present bias is so large that Self 1 requires a very large loan size to discipline her investment actions then she will not invest and prefer to earn the alternative income w' in period 3. In this case, she might borrow however, this borrowed amount is just used for smoothing her consumption profile across periods 2 and 3.

$$\delta\Big[u(w+l(\delta)-k)+u(b-(1+r_b)l(\delta))\Big] >= \max_l \delta\Big[u(w+l)+u(w'-(1+r_b)l\mathbb{I}_{l>=0}-l\mathbb{I}_{l<0})\Big] \tag{3.33}$$

(iii) Since, $u(.)$ is an increasing, concave, differentiable utility function, it is easy to show that the $l(\delta)$ is strictly decreasing in δ when $\delta > \hat{\delta}$. Note that here, $l(\hat{\delta}) = l^*$ and $l(\delta)$ is the over-borrowed loan amount which satisfies the incentive compatibility constraint for Self 2 when her hyperbolic discount factor is δ.

□

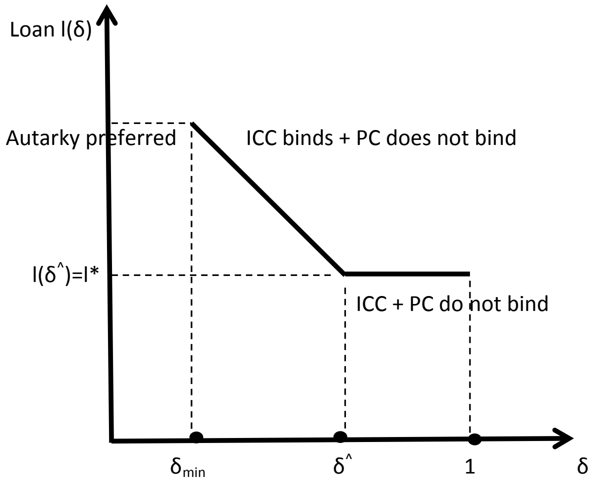


Figure 3.3: Optimal contracting: Time inconsistent borrower and non-profit MFI

3.4 Relation to experimental evidence

While the size of the microcredit industry has significantly grown in the past decade across the world, researchers have very little rigorous evidence on whether microcredit actually benefits the poor. For instance, recent experimental evidence hasnt been able to determine what the different uses of microloans are by poor borrowers. Are microloans mostly used for consumption purposes or are they used for entering new and profitable businesses or are they used for expanding their existing businesses.

To evaluate the impact of microcredit programs, researchers have to control for both borrower and lender self-selection issues and they cannot simply compare the wealth, consumption and investment decision making of MFI clients versus non-clients. Till now, only 6-7 randomized evaluation studies have been conducted by different research teams across different countries like Morocco, India, Bosnia-Herzegovina, Mexico, Mongolia and Ethopia.

Banerjee, Duflo, Glennerster, and Kinnan (2015) perform a controlled experiment in which micro-credit is randomly offered through a large India MFI (Spandana) to half of the poor neighborhoods in Hyderabad, India. Prior to this intervention, majority of the households in these poor neighborhoods did not have access to formal finance and borrowed from informal sources (like moneylenders, family and friends). The typical loan is a group-liability loan and the loan size ranges from 200 USD. Group members are eligible for larger loan sizes (till 240 USD) after all the group loans have been paid. Following this intervention, the authors collect household survey data from these neighborhoods to compare several aspects of borrower and non-borrower behavior both across the treatment and the control areas. Firstly, the authors compare microfinance take-up rates and evaluate whether this intervention increases the supply of credit to constrained borrowers in treatment regions. They find some evidence for this overall take-up rates are not very high but slightly higher in treatment regions than controlled regions. One and half years (three and half years) after the intervention, take-up rate is 26.7% (38.5%) amongst treated households and 18.3% (33%) amongst controlled households.[9] The overall borrowed amount does not increase significantly and poor households tend to substitute informal loans with microloans. The authors then compare consumption decisions and find that treated poor households tend to spend more on durable goods than non-durable good but, their total consumption expenditure does not increase significantly. Finally as far as borrowers investment decisions are concerned, the authors find that while the profitability of the most productive enterprises increases, the profits of the marginal enterprise slightly decrease after the intervention. Therefore, heterogeneity in borrower project returns is an important issue to consider while evaluating the impact of microcredit programs.

One thing to be worried about in the above study is the low differential between the take-up rates of treated and controlled households. Another aspect that prior studies have not controlled for are separating the direct from the indirect effects of microcredit programs. The direct effect of microcredit programs would be on the most interested but constrained set of borrowers whereas the indirect effects would be for other borrowers as well through general equilibrium effects or anticipation of increase in future microcredit etc. To ensure that

[9]The take-up rate is positive amongst controlled households due to the entry of other MFIs (not Spandana) who also offered microloans to these neighborhoods over the evaluation period.

the impact of microcredit is estimated more precisely, Crepon, Devoto, Duflo, and Pariente (2015) conduct a controlled experiment through a partner MFI (Al Amana) in a rural area of Morocco. The MFI only offers group-liability loans with frequent repayment and the size of the loan ranging from 120 to 1900 USD per member. No other MFIs operated in these areas, both prior to and during the intervention period therefore supply of credit is strictly higher for treated households than for controlled households. Also, the authors gather survey evidence to identify ex-ante the most interested households within these regions and are thus able to separate the direct effect of microcredit on the most interested households versus the indirect effects on other households. After controlling for these aspects, the authors firstly find that the take-up rate of microfinance is quite low (only 13-17%) across treated households. Secondly, they find that treated households generate significantly higher profits from their small business activities (agriculture and animal husbandry are the most widely observed activities) however, like Banerjee, Duflo, Glennerster, and Kinnan (2015), these effects are quite heterogeneous across borrowers. The lower tail of profits generated from treated household business activities is observed to be negative. Thirdly, borrowers tend to supply more labor to own business activities than to the outside labor market thus decreasing their overall wage income. Finally, no changes are observed in overall consumption expenditure of borrowers.

Angelucci, Karlan, and Zinman (2013) conduct a large-scale clustered randomized trial that substantially expands the access of microcredit to poor households in north-central Sonora, Mexico through Compartamos Banco (which is the largest MFI in Mexico). As part of the study, the MFI randomly promoted microcredit across treated regions and after the promotion and extension of microcredit, survey evidence was collected by the authors for a section of these households/businesses for the following three years. Using the survey evidence, firstly the authors find that the take-up rate of microcredit is slightly higher across the treated regions (18.9% versus 5.8%) suggesting that the increased supply of credit may have relaxed the credit constraints of treated borrowers. Secondly, the average treatment effects are significantly positive for 8 of the 34 outcomes that they collect information for (both business investment increases and a smoother consumption profile is observed for treated households.) Thirdly, the quantile treatment effects are estimated and it is found that there are significantly positive effects on the right tail of most outcomes. Therefore similar to the previous studies, these findings suggest that the impact of microcredit programs is positive and significant for some borrowers however, it may not be able to completely eradicate poverty as the effects are quite heterogeneous across borrowers.

From a policy perspective, rather than expanding the access of MFIs across all poor borrowers it is important to experimentally determine the features of the optimal contract. For instance, randomized controlled studies can be designed to evaluate the effects of changes in loan interest rates, loan sizes, loan repayment frequency etc. on the investment and consumption decision making of treatment households. This will give us a more informed understanding of what the plausible impacts of microcredit are for poor borrowers.

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