ABSTRACT

Title of dissertation: ESSAYS ON FIRM FINANCING, INVESTMENT, AND GROWTH

Veronika Penciakova
Doctor of Philosophy, 2019

Dissertation directed by: Professor Şebnem Kalemli-Özcan
Department of Economics

This dissertation studies the relationship between firm financing, investment, and growth. Chapter 1 makes use of a unique dataset that combines ownership data, Census Bureau data, and patenting data to study whether firms held by owners with more diversified business interests engage in more growth-enhancing risky innovation. I document that higher owner diversification leads to riskier innovation, after taking into account firm life cycle characteristics, access to finance, other features of ownership structure, and inherent firm and owner characteristics. I also provide evidence that diversification matters at the sector level, with sectors characterized by higher diversification exhibiting higher risky innovation, revenue, volatility, and growth. I present a stylized model that rationalizes these empirical findings.

Chapter 2 studies the financial leverage of U.S. firms over their life-cycle and the implications of leverage for firm growth and response to shocks using a new dataset that combines private firms' balance sheets with Census Bureau data. We show that firm age and size are good predictors of leverage for private firms but not

for publicly-listed ones. Using the Great Recession as a shock to financial conditions, we show that during the Great Recession leverage declines for private, but not public firms. We also provide evidence that private firms' growth is positively associated with leverage, while public firms' growth is not.

Chapter 3 explores the extent to which interest rate fluctuations during sudden stops contribute to resource misallocation and explain the sharp decline in productivity observed during these episodes. Using firm-level data from Chile, I show evidence of rising misallocation during the 1998 sudden stop and evidence of hiring and investment frictions that could trigger this rising dispersion and subsequent decline in productivity. I then study the contribution of interest rate level and volatility shocks to this rise in misallocation using a small open economy model featuring heterogeneous firms that are subject to non-convex capital and labor adjustment frictions and calibrated using firm-level data from Chile. The model is qualitatively consistent with the rise in dispersion of marginal products and the decline in productivity observed during the sudden stop crisis.

ESSAYS ON FIRM FINANCING, INVESTMENT, AND GROWTH

by

Veronika Penciakova

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2019

Advisory Committee:
Professor Şebnem Kalemli-Özcan, Chair
Dr. Emin Dinlersoz
Professor John C. Haltiwanger
Professor Felipe Saffie
Professor Liu Yang

Dedication

To Erika, Juraj, and Matej

Acknowledgments

I am deeply grateful for the many people who supported me throughout this journey. This dissertation would not have been possible without them.

I am indebted to my dissertation committee. I want to thank my advisor, Sebnem Kalemli-Ozcan, for her invaluable guidance throughout the years. She has invested much time and effort in shaping me into the researcher I am today. She has imparted invaluable insight and advice on my research, provided countless opportunities for professional development, encouraged me to take risks, and supported me in my endeavors.

I am grateful to Felipe Saffie who has provided unique perspective and guidance on my research, helped me see the forest from the tree, and always reminded me to keep pushing. I thank Emin Dinlersoz for his mentorship over the years and the countless conversations that have aided me in my research and navigation of Census Bureau data. I thank John Haltiwanger for challenging me to think deeply about the details and for providing insights that helped elevate my research. I also thank Professor Liu Yang for her support and encouragement during the job market and for serving on my dissertation committee.

I am forever grateful to Boragan Aruoba, Felipe Saffie, Bora Durdu and John Shea. Thank you for believing in me. The completion of this dissertation would not have been possible without your support. I thank faculty members, especially Guido Kruesteiner, Nuno Limao, and Luminita Stevens whose helpful comments helped improve my research.

I am also grateful for my colleagues at the Center for Economic Studies. In particular, I benefited immensely from the insights and support of Emek Basker, Lucia Foster, Nathan Goldschlag, Henry Hyatt, Shawn Klimek, Javier Miranda, Scott Olmacher, Martha Stinson, and Cristina Tello-Trillo. Thank you for answering countess questions about the data and for the endless entertainment of CES lunches.

My friends and colleagues at the University of Maryland have been instrumental in this journey. A special thank you to my graduate mentors, Jake Blackwood, Joonkyu Choi, and David Moreno, for helping me navigate the graduate program and for spending hours refining the first three slides of each of my presentations. I am grateful for Ian Chadd, Rodrigo Heresi, Karam Jo, Seth Murray, Matt Staiger, and Cody Tuttle for your years of support and friendship. From practice presentations to conversations over cups of coffee, you have challenged and supported me and kept me sane. I am also thankful for the economics department staff members, especially Terry Davis, Vickie Fletcher, Emily Molleur, Amanda Statland, and Mark Wilkerson. Your help and words of encouragement are immensely appreciated.

I am eternally grateful to the mentors that encouraged and guided me towards getting a PhD. I thank Dana Stryk for introducing me to the field of economics, and Daniel Kaufmann for challenging me to speak up and take a seat at the table. And a special thank you to David Allen Grier who has helped me navigate this windy path for over a decade.

I am thankful for the support of my friends and family. Alana, Christina, Ella, Gillian, Kelly, Krysta, Lindsey, Liz, Maegan, Meg, Megan, and Steph, I am forever grateful for the comfort and encouragement you provided throughout this journey. A special thank you to Alana and Megan for being my family and support as I first set out on this path, to Liz and Lindsey for starting this journey with me as strangers and ending it as family, and to Kelly, Gillian, and Meg for being my sanity during this insane time.

Austin, I love you dearly. Thank you for being my biggest cheerleader, taking care of me, making me laugh constantly, comforting and grounding me, and being my home during the most difficult part of this journey.

Above all, I thank my family, Erika, Juarj, and Matej. Your love never waivers, your support never falters, and your encouragement never quiets. You have always believed in me and encouraged me to forge my own path. You have stood by me through it all. I would not be me and none of this would be possible without you. I love you.

Disclaimer

Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

Preface

Investment, innovation, and the efficient allocation of resources play a central role in driving economic growth. A critical determinant of the amount and type of investments firms make is their ability to access financial resources. This dissertation contributes to three extensive bodies of literature that study the influence of ownership, bank financing, and financial shocks on firm investment and growth. In the three chapters, I study how owner diversification, financial leverage, and sudden stops affect the investment decisions of firms, and consequently how they affect firm, sectoral, and aggregate outcomes.

In chapter 1, I ask whether firms held by owners with more diversified business are more likely to innovate outside of their existing area of technological expertise. This type of innovation lying outside of a firm's core business, while risky, has been found to contribute disproportionately to aggregate growth (Akcigit and Kerr (2018)). I build off the insights of a long-standing literature that emphasizes the relevance of ownership structure for investment (Jensen and Meckling (1976), Fama and Jensen (1983), Shleifer and Vishny (1986), and Holmstrom and Costa (1986)) and the importance of diversification opportunities for risk-taking (Obstfeld (1994) and Acemoglu and Zilibotti (1997)). I fill a gap in the existing empirical literature that has not directly examined the relationship between diversification and risky innovation, and rationalize my empirical findings through a stylized model that highlights how diversification incentivizes risky investment through risk-sharing.

I construct a unique dataset that combines ownership data from Moody's Bureau van Dijk with patenting data from the USPTO and other firm-level data from the U.S. Census Bureau. Using the ownership data, I measure owner diversification as the total number of firms an owner controls. Following Akcigit et al. (2016), I use patenting data to construct a measure of risky innovation as the technological distance between a firm's new patents and its existing patent portfolio. I then document that higher owner diversification leads to riskier innovation.

In particular, I exploit the richness of the data and account for firm life-cycle characteristics, access to finance, and other features of the firm ownership structure. I rule out that the positive relationship between diversification and risky innovation is driven by more diversified owners targeting inherently riskier firms for acquisition by taking advantage of the panel nature of the data and controlling for firm fixed effects. I rule out that the positive relationship is driven by higher ability owners being better able to identify diversification and innovation opportunities by controlling for owner fixed effects. And I rule out that the positive relationship is entirely driven by higher risky innovation incentivizing owners to become more diversified by showing the firms held by initially more diversified owners undertake riskier innovations. I then exploit cross-sector variation in owner diversification and outcomes to emphasize the aggregate importance of the risk-sharing channel. I show that sectors characterized by higher diversification exhibit riskier innovation, are larger and more volatile, and grow faster.

To rationalize these findings, I construct a stylized model featuring risk-averse owners that are differentiated by their degree of diversification and choose how much risky, productivity-enhancing investment to undertake in their portfolio of firms. The outcome of this investment is uncertain and uncorrelated across firms.

The first feature creates a tradeoff for owners because higher investment is associated with both higher potential returns and a higher gap between success and failure. The second features creates safety in variety. As a consequence, the risk-sharing channel is active and more diversified owners choose riskier investments. Through the findings documented in Chapter 1, I establish owner diversification as an important factor incentivizing riskier, growth-enhancing, innovation.

In chapter 2, which is joint work with Emin Dinlersoz, Sebnem Kalemli-Ozcan, and Henry Hyatt, we study how firms' access to finance evolves over their lifecycle, and evaluate the implications of financial leverage for firm growth and responsiveness to financial shocks. Little is known about how U.S. firms finance their growth due to the limited availability of financial data for privately-held firms. Yet, these private firms are the most likely to face the financial frictions emphasized by Schliefer and Vishny (1992), Holmstrom and Tirole (1997), Kiyotaki and Moore (1997), Bernanke and Gilchrist (1999), Cooley and Quadrini (2001), Albuquerque and Hopenhayn (2004), Moll (2014), and other. Understanding the consequences of financial frictions for these firms is critical for understanding the firm-level and aggregate impacts of financial shocks (Gertler and Gilchrist (1994), Khan and Thomas (2013), Chodorow-Reich (2014), Buera and Moll (2015), Giroud and Mueller (2017), Gopinath et al. (2017), Gilchrist et al. (2018)). We contribute to these strands of literature by constructing a new dataset that combines the balance sheets of publicly-listed and privately-held firms with other firm-level data from the U.S. Census Bureau, which allows us to study the financial leverage dynamics of U.S. firms.

We first document a series of stylized facts. Conditional on age, large private firms have higher short-term and long-term leverage and lower equity as a fraction of their assets. Conditional on size, young private firms have higher leverage and lower equity. By exploiting the panel nature of the data, we show that private firms become more leveraged as they grow over time. These dynamics are quite different among publicly-traded firms. Conditional on age, large public firms have lower short-term leverage and higher long-term leverage, suggesting a compositional shift in debt maturity as these firms grow. The equity-size relationship exhibits an inverted-U shape, providing further support for compositional shifting. Conditional on size, the relationship between all measures of leverage and age is weak among public firms, and the age-equity relationship is weakly negative. Moreover, firm size has no effect on short-term or long-term leverage within public firms over time.

We then exploit the Great Recession as a financial shock. We find that among private firms, both small and large firms are forced to deleverage during the crisis and that short-term leverage is more affected than long-term leverage. Meanwhile, the leverage of small and large public firms is unaffected by the financial crisis. Finally, we study the relationship between bank financing and growth. In both cross-sectional and panel specifications, we show that short-term leverage is positively associated with revenue growth among private firms, while its effect is attenuated and even negative among public firms. The findings of Chapter 2 emphasize the need to account for the financial constraints faced by U.S. private firms when evaluating the implications of financial frictions for firm-level and aggregate outcomes.

In chapter 3, I explore whether interest rate shocks worsen resource allocation and contribute to the fall in productivity observed during sudden stops. Over the past three decades, emerging economies have experienced a series of sudden stops that are characterized by large capital outflows and spikes in the real interest rate. These crises result in short-run falls in output, investment, and productivity. The small open economy literature has proposed several explanations for these declines in producutivity. Ates and Saffie (2016) and Queralto (2018) focus on the effect of interest rate shocks on firm entry, while Meza and Erwan (2007) study factor utilization and Pratap and Urrutia (2012) emphasize resource misallocation across sectors. I focus on a complementary channel, within sector resource misallocation arising from capital and labor adjustment frictions.

Using data on manufacturing firms in Chile, I adopt the Hsieh and Klenow (2009) framework and show that the dispersion of marginal products of capital and labor rose during the 1998 sudden stop. These findings suggest that resource reallocation across firms slowed during the crisis. To understand a potential source of this slowdown, I show that the share of firms delaying investment and hiring rose substantially during this period. When firms face hiring costs and investment is partially irreversible, an increase in the level or volatility of the interest rate slows down the responsiveness of firms to demand shocks. This slowdown manifests itself as an increase in the dispersion of marginal products and a fall in productivity.

I then take a structural approach in order to quantify the contribution of these adjustment frictions to the fall in productivity during a sudden stop episode. I build a small open economy industry equilibrium model featuring heterogeneous firms that are subject to capital and labor adjustment frictions, and an exogenous interest rate process that is subject to level and volatility shocks. I calibrate the model using

Chilean data and show that interest rate level and volatility shocks trigger declines in investment, hiring, and output, as well as increases in the dispersion of marginal products and decline in aggregate productivity. The model is qualitatively consistent with my empirical findings, but explains only a small fraction of the observed decline in productivity. The results of chapter 3 highlight that along with firm entry, factor utilization, and cross-sector resource reallocation, within-sector resource reallocation contributes to the declines in productivity observed during sudden stop episodes.

Table of Contents

List of Tables

List of Figures

Chapter 1: Diversification & Risky Innovation among U.S. Firms

1.1 Introduction

An extensive literature establishes innovation as a critical engine of sustained development, and emphasizes the disproportionate contribution of "risky innovation" to growth. Akcigit and Kerr (2018) find that 80% of the aggregate growth due to innovation is driven by innovation lying outside a firm's existing area of technological expertise. The factors that incentivize firms to engage in this type of innovation are not yet fully understood. The literature considers investments made outside a firm's core business as risky, and recognizes ownership structure as an important determinant of firm risk-taking. In this paper, I study the impact of owner diversification on the innovation decisions of firms. More specifically, I examine whether firms held by owners with more diversified business interests undertake riskier innovations, assess the relevance of the risk-sharing channel, and evaluate whether the firm-level relationship has implications for sector level outcomes.

The intuition connecting owner diversification and risky investment is straightforward. When firm owners are risk averse, their expected utility falls as the variance of their wealth rises. For this reason, a well diversified owner is more risk tolerant because she shares firm-specific risk across her portfolio (Obstfeld (1994) and Acemoglu and Zilibotti (1997)). The literature refers to this mechanism as the ”risk-sharing channel.” Innovation is an important type of risky investment that entails a high level of uncertainty and potentially high payoffs. These risks are magnified when firms venture into new technological areas.

Existing empirical studies have not directly examined the relationship between owner diversification and risky innovation and have not tested the risk-sharing channel. The literature connecting diversification to firm risk-taking often conflates diversification with other, confounding features of ownership structure, such as ownership concentration. This literature does not focus on innovating firms and only examines noisy, volatility-based measure of riskiness, which only indirectly correspond to the risky investments emphasized in the theoretical literature. The empirical literature on innovating firms and organizational structure focuses on innovation intensity and quality, rather than riskiness, and has paid little attention to diversification. Due to data limitations the existing literature studies non-representative samples of firms, with U.S. studies relying on publicly-listed firms. Existing empirical studies also rarely concern themselves with the aggregate implications of firm-level findings.

In this paper, I tackle the gap in the empirical literature. I construct a unique dataset that combines Moody’s Bureau van Dijk (BvD) global ownership data for a sample of privately-held and publicly-listed U.S. firms with the Census Bureau’s Longitudinal Business Database (LBD), Compustat, and USPTO patenting data. The resulting data contain 38,000 firm-owner-year observations between 2007 and 2013, the majority of which belong to privately held firms. Using data from privately held firms is important because until recently publicly listed firms have been the sole focus of research in the United States.

The newly constructed data set has several advantages. The BvD global ownership data allow me to identify the ultimate owner of each firm as the owner holding the largest fraction of the firm's equity in a particular year. For each owner-firm pair, the ownership data also help disentangle owner diversification from other potentially confounding features of ownership structure, such as ownership concentration. Owner diversification captures how many firms an owner holds in her portfolio and ownership concentration captures the fraction of equity she control in each of these firms. Theory predicts that the positive relationship between diversification and risky investment arises from risk-sharing. The relationship between concentration and risky investment is ambiguous. On the one hand, closely held firms may be subject to fewer agency frictions, which incentivizes risk-taking (Jensen and Meckling (1976) and Shleifer and Vishny (1986)). On the other hand, in closely held firms owners extract private benefits, which disincentivizes risk-taking (Fama and Jensen (1983), Holmstrom and Costa (1986), and Hirshleifer and Thakor (1992)). Yet, owner diversification and ownership concentration are often conflated in the literature because they are assumed to be strongly negatively correlated, which is not borne out in the data. By distinguishing between the two, I isolate the influence of owner diversification.

The Census Bureau firm-level data provide information on important firm life-cycle characteristics including firm age, employment, and industry. These allow me to control for time-varying firm characteristics that are simultaneously associated with risky innovation and owner diversification. Moreover, the data allow me to address sample selection directly. Unlike other empirical studies, I identify dimensions along which the raw analysis sample is not representative, construct sampling weights using logistic regression, and use these weights in subsequent analysis. I therefore make inferences about the relationship between diversification and risky innovation for the representative patenting firm in the United States and about the importance of owner diversification for sector-level outcomes.

The USPTO patenting data enable me to construct a direct measure of risky innovation that improves upon the volatility-based measures of riskiness favored in the empirical literature. Following Akcigit et al. (2016), I first measure the technological distance between any two patent classes, and then define risky innovation as the average technological distance between each firm's new patents and its existing patent portfolio. I validate the measure of riskiness by verifying that it is positively associated with revenue growth and volatility. A 10% increase in risky innovation is associated with a 0.6 percentage point increase in revenue growth and a 0.2% increase in revenue growth volatility. I also augment the data with Compustat in order to identify firms that are publicly traded. Because innovation often requires external financing, the publicly-listed status of firms proxies for access to finance.[1]

Using the merged data, I first document a strong statistically significant positive relationship between owner diversification and risky innovation, after addressing sample selection, including a rich set of industry-year fixed effects, and holding constant firm life-cycle characteristics, financial structure, prior risky patenting behav-

[1]Recent studies (Asker et al. (2015) and Dinlersoz et al. (2018)) have found evidence that publicly-listed firms are less financially constrained than privately-held firms.

ior, and other features of the firm's ownership structure. A one standard deviation increase in owner diversification is associated with a 5% increase in risky innovation. The results are robust to alternative measures of both diversification and risky innovation. In particular, the positive relationship holds when diversification is measured by the number of unique industries in which the owner is active, and the degree to which activity is dispersed across these industries. The relationship also holds when the risky innovation is measured as the distance between a firm's new patents and the *owner's* portfolio, which accounts for the possibility that when firms innovate outside of their area of expertise they innovate within their owner's area of expertise. This baseline approach goes far in addressing selection on observables, but unobserved heterogeneity precludes a causal interpretation.

Owner diversification may be correlated with unobserved firm characteristics, such as a firm's inherent riskiness. For instance, the baseline relationship can result from more diversified owners acquiring firms with riskier profiles, rather than diversified ownership incentivizing firms to engage in riskier innovation. If this were the case, changes in owner diversification should not be associated with changes in innovation behavior. First differences control for the underlying risk profile of firms, as well as other time-invariant firm characteristics. The first difference approach confirms the positive relationship between changes in owner diversification and changes in risky innovation within firms over time.

However, the first difference specification does not account for inherent owner characteristics. The existing literature emphasizes the importance of individual ability and past experience as influencing entrepreneurial decisions. For instance, higher ability investors may be better equipped to take advantage of both diversification and innovation opportunities. To rule out this possibility, I focus on the sub-sample of firms that are held by the same owner over the entire period. By focusing on this sub-sample in a first-difference estimation, I also control for time invariant owner effects. I find that even after accounting for both time invariant firm and owner characteristics, higher owner diversification leads to riskier innovation. This relationship can be interpreted as causal if owner diversification and the remaining unobserved time-varying firm and owner characteristics that are summarized in the error term are orthogonal.

An alternative interpretation of the positive relationship is that it arises from more risky innovation incentivizing owners to diversify in order to offset the increased risk they face. First, while possible, it is unlikely that the innovation decisions of firms are the sole reason owners acquire or sell other firms in their portfolio. Second, to formally address this story of reverse causality, I focus on a balanced sample of firms that are held by the same owner throughout the period, calculate changes in risky innovation and other time varying firm-level controls over a three year horizon, and measure owner diversification and ownership concentration at the beginning of the period. The initial conditions specification confirms that changes in risky innovation are higher among firms held by initially more diversified owners than among those held by initially less diversified owners. This specification controls for time varying and time invariant firm characteristics, and shuts down the dynamics feedback from riskier innovation leading to higher owner diversification.

The first difference and initial conditions specifications are complementary.

The first difference specification shows that the relationship between owner diversification and risky innovation is not driven by time invariant firm and owner characteristics. The initial conditions specification shows that the positive relationship persists when the feedback from risky innovation to owner diversification is shut down. Even in the presence of remaining questions regarding the identifying assumptions, my paper documents new findings about the relationship between owner diversification and risky innovation among U.S. firms. These findings highlight the role of owner diversification in facilitating risky innovation, and provide a springboard for studying whether this relationship is consistent with theories of risk-sharing, and whether it survives aggregation and has implications for sector-level outcomes.

Theory suggests that the mechanism underlying the positive relationship between diversification and risky-innovation is risk-sharing. I evaluate this mechanism by taking advantage of variation in owner types. Owners can be classified as individuals, companies, or institutional owners (mutual funds, pension funds, etc.). Individual owners are relatively more exposed to the risk arising from firm-level innovation decisions than companies due to the limited liability of the latter, and institutional owners are least exposed since they manage portfolios on behalf of other investors. Consistent with the risk-sharing mechanism, I find that the relationship between diversification and risky innovation is strongest for firms held by individual owners.

I test whether the positive firm-level relationship between owner diversification and risky innovation has aggregate implications by exploiting cross-sector variation in diversification, innovation, and revenue. For each sector, I calculate average owner diversification, average risky innovation, total risky innovation, total revenue, and revenue growth in each year. Sectors characterized by higher diversification are characterized by higher average and total risky innovation, total revenue, and revenue growth. The results are robust to the inclusion of fixed effects that neutralize the effects of aggregate conditions and industry-specific differences in diversification and outcomes. In particular, a 10% increase in sector-level diversification is associated with 4.4% more risky innovation, 1.2% higher total revenue, and 0.3 percentage point higher revenue growth rate.

My empirical findings show that diversification facilitates risky innovation. Yet, the endogenous growth and firm dynamics theoretical literatures leave no role for the risk-sharing channel that underpins the observed relationship. The endogenous growth literature features firms that hold a portfolio of products, but the commonly imposed risk-neutrality assumption leaves no role for risk-sharing. Meanwhile, the firm dynamics and experimentation literature features risk averse agents, but does not allow owners to control more than one firm, leaving no opportunity for diversification.

To rationalize my empirical findings and highlight the model ingredients needed to activate the risk-sharing channel, I construct a stylized, static, single-agent model featuring risk averse owners, who can hold multiple firms, and face risk arising from investment decisions. More specifically, risk averse owners differ in their degree of diversification. Each owner chooses how much productivity-enhancing investment to undertake in her portfolio of firms. Critically, the outcome of this investment is uncertain and uncorrelated across firms. With some probability the investment is successful and contributes positively to productivity. If the investment is unsuccessful, productivity declines. Higher investment is associated with higher returns in when investment is successful, but also with a larger gap between success and failure. Because success is uncorrelated across firms, owners find safety in variety. An owner holding more firms shares idiosyncratic risk across her portfolio and chooses riskier investment. The model also highlights the relevance of owner diversification in high uncertainty environments. Intuitively, as the probability of success approaches one, the investment decisions of more and less diversified owners converge since the benefits of risk-sharing decline as investment outcomes become more certain. I verify that diversification has qualitative implications for aggregate outcomes by conducting a simple partial equilibrium aggregation exercise. By comparing the investment and output of of sectors composed of firms held by owners with different degrees of diversification, I show that sectors characterized by higher diversification feature higher investment and output.

The remainder of this paper is organized as follows. Section 1.2 discusses this the existing literature. Section 1.3 describes the data and variable construction. Section 1.4 discusses the empirical approach and reports results. Section 1.5 describes the stylized model and implications. Section 1.6 concludes.

1.2 Literature

This paper contributes to two strands of the empirical literature. The first strand examines whether ownership structure influences firm risk-taking and finds mixed evidence. This literature measures firm risk as the volatility of stock prices or operating revenue. As a consequence, the literature cannot disentangle the specific types of risky investment strategies firms engage in, such as innovation. The mixed results highlight the importance of addressing sample selection and distinguishing between different features of ownership structure. Wright et al. (1996) and John et al. (2008) focus on ownership concentration and find no significant relationship with risk-taking among publicly-listed U.S. firms when concentration is measured by the presence of large blockholders or the equity stake of owners. Paligorova (2010) also measures concentration as fraction of equity controlled by the owner, but documents a positive relationship in a global sample of public and private firms. Sraer and Thesmar (2007) proxy for concentration and find that family owned firms outperform firms with more disperse ownership. Anderson and Reeb (2003) also analyze family ownership but consider it a proxy for low diversification and find it to be associated with higher operating risk. Other studies use alternative proxies for diversification and document a positive relationship with riskiness. These include Thesmar and Thoenig (2011) who distinguish between diversified listed and undiversified private firms; Kalemli-Ozcan et al. (2014) who proxy diversification with foreign ownenrship; and Faccio et al. (2011) and Lyandres et al. (2018) who measure diversification as the number of firms held by the owner.[2] I confront the limitations of this literature by measuring ownership concentration and owner diversification separately, similar to Faccio et al. (2011) and Lyandres et al. (2018) and addressing sample selection

[2] As in Thesmar and Thoenig (2011), Davis et al. (2006) document similar differences in the volatility of private and listed firms for the United States without linking the findings directly to owner diversification.

directly using the LBD. I further contribute by focusing on the important, but understudied subset of innovating firms, and moving beyond indirect volatility-based measures of firm risk.

A second strand of empirical literature evaluates the relationship between organizational structure and innovation, but rarely emphasizes diversification or risk-taking. Several papers study venture capital funding. Kortum and Lerner (2000), Tian and Wang (2014), Bernstein et al. (2016a), and Akcigit et al. (2018) find that VC funding is associated with more and higher quality patenting by funded firms. Others focus on private equity investment. Hall (1990) finds that leveraged buyouts (LBDOs) have little impact on innovation. Lichtenberg and Siegel (1990) and Lerner et al. (2011) document a positive relationship between LBOs, R&D expenditure, and patent quality. A couple focus on firms' listed status. Bernstein (2015) finds that firms shift towards acquiring new technologies following their IPO; and Phillips and Sertsios (2017) finds that innovation in public firms is more responsive to changes in financing. Several papers focus on institutional ownership. Francis and Smith (1995), Eng and Shackell (2001), and Aghion et al. (2013) find that institutional ownership is associated with higher R&D investment and productivity. Yet, none study owner diversification. I focus on the role of diversification in influencing the innovation decisions of firms, and move beyond the measures of R&D expenditure and efficiency and patenting intensity and quality favored in the literature by emphasizing risky innovation.

This paper also advances the theoretical literature. My empirical results highlight a role for owner diversification in facilitating risky innovation. Existing models of endogenous growth and firms dynamics leave little room for the risk-sharing channel. Recent research in the endogenous growth literature focuses on the importance of incumbent innovation (Acemoglu and Cao (2015), differences in innovative capacity (Acemoglu et al. (forthcoming) and Ates and Saffie (2016)), and drivers of heterogeneous innovation (Akcigit and Kerr (2018) and Acemoglu et al. (2017)).[3] Small firms (Akcigit and Kerr (2018)) and those open to disruption (Acemoglu et al. (2017)) are more likely to undertake radical innovations. The firms in this literature are characterized by a portfolio of products and are assumed to be risk neutral, which leaves no role for risk-sharing. In the firm dynamics literature, Vereshchagina and Hopenhayn (2009) show that poor risk-averse entrepreneurs choose to undertake risky projects. In Choi (2017) risk-averse entrepreneurs with higher outside options in paid employment engage in riskier activities. And Celik and Tian (2018) emphasize better corporate governance and incentivized CEO contracts as drivers of disruptive innovation. Although the entrepreneurs in this literature are risk-averse, because they own only one firm there is no role for diversification. The stylized model described in section 1.5 contributes to this literature. It incorporates risk-averse owners who can hold multiple firms and make risky investment decisions. The model rationalizes the positive relationship between diversification and risky innovation documented in the data.

[3]The recent literature builds off work of Grossman and Helpman (1991), Aghion and Howitt (1992),Kortum (1997), Howitt (1999), and Aghion et al. (2001), Klette and Kortum (2004), and Lentz and Mortensen (2008). The recent literature also builds off the influential research by Romer (1986), Romer (1990), and Jones (1995) in which growth arises from expanding varieties.

1.3 Data and Measurement

1.3.1 Data set construction

To study the importance of the risk-sharing channel for innovation among U.S. firms, I construct a new data set and test whether firms held by more diversified owners engage in riskier patenting. I combine the LBD from the U.S. Census Bureau with ownership data from Moody's Bureau van Dijk (BvD), patenting data from the USPTO, and firms' publicly listed status from Compustat. These four data sources are combined using employer identification numbers (EINs) and probabilistic name and address matching.[4]

The Longitudinal Business Database (LBD) tracks all non-farm private businesses with at least one paid employee from 1976 through 2015. A business (or establishment) corresponds to the physical location where business activity occurs. Establishments that are operated by the same entity, identified through the Economic Census and the Company Organization Survey, are grouped under a common firm identifier. Firm size is measured by total firm-level employment. Firm age is based on the age of the oldest establishment of the firm when the firm is first observed in the data.[5] Industry of operation is based on the NAICS code associated with the highest level of employment.[6] Firm revenue is measured in constant USD,

[4]For this paper, I match LBD records with BvD records. The match between LBD and Compustat was generated as a part of Dinlersoz et al. (2018). The match between LBD and USPTO data was kindly provided by Nikolas Zolas from the U.S. Census Bureau.

[5]Based on this definition, all existing firms in 1976 (when the data series begins) are classified as age 0 in that year. This results in left-censoring of the age variable. In regression analysis, I include a dummy variable that identifies left-censored firms.

[6]NAICS codes are based on time-consistent industry classifications developed in Fort and Klimek (2018).

where the GDP Implicit Price Deflator is used to convert nominal to real values.[7]

Ownership data are obtained from Moody's BvD global historical data and span 2007 through 2016. Information on firms and their owners are gathered from a variety of sources including official registers, regulators, annual reports, company websites, and correspondences. As a consequence of regulations, in the United States much of the data derive from SEC filings. If a public or private company registers its equity securities under the Exchange Act, then any shareholder who holds 5% of shares or more is required to file beneficial ownership reports as long as their holdings remain at or above 5%. The filings contain information on the shareholder and her future investment intentions.[8] The data therefore primarily include shareholders with at least 5% equity stake in the firm. In this paper, I focus on the characteristics of firms' largest owner(s) so not observing shareholders controlling less than 5% of the firm does not present a challenge.

For each firm in a particular year, the data contain a list of owners, their country of origin, owner type (individual, industrial company, bank, mutual fund, etc.), fraction of equity controlled (used to measure ownership concentration), and type of relationship (immediate shareholder, domestic ultimate owner, global ultimate owner, etc.). I focus on U.S. firms and their owners (both domestic and foreign), but the BvD data has global coverage of over 150 countries. Existing empirical literature emphasizes the importance the largest shareholders for firm outcomes (Faccio et al. (2011), Paligorova (2010)). I therefore focus on the characteristics of the share-

[7]For information on the construction of the revenue variable, see Haltiwanger et al. (2017).

[8]Information on reporting requirements associated with ownership can be found at the SEC website (link).

holder(s) who BvD identifies as the global ultimate owner with at least 25% equity stake. More specifically, in a given year BvD identifies this global ultimate owner(s) as the domestic or foreign shareholder who controls the largest fraction of the firm's equity. The 25% threshold helps exclude cases where the ultimate owner is unlikely to have influence over the firm's decisions because of her low equity stake. For this ultimate owner, I directly observe the level of ownership concentration in the firm and use the global nature of the BvD data to track her level of diversification. In some cases, BvD identifies multiple shareholders as global ultimate owners in one firm in the same year. This arises in cases of joint ownership. If BvD identifies multiple global ultimate owners, I keep those owners that have an equity stake in the ballpark of 50% (between 40% and 60% equity). In these cases, I track the owner diversification and ownership concentration of multiple owners for the same firm. I use the global nature of the data to construct owner diversification, which measures the total number of firms held globally by an owner in a particular year. The BvD data also contain the EIN, firm name, street address, city, state and zip code for firms in the sample.[9] This additional information is used in linking BvD data to the LBD.

I augment the LBD-BvD linked data with two additional sources. Patenting data are obtained from PatentsView, which is derived from USPTO data files between 1976 and 2015. These data contain patent-level information including application and grant dates, assigned technology class, number of citations made to and

[9]The full set of information – EIN, name, address, city, state and zip code – is not available for every firm. I use whatever information is available for a firm in the linking procedure. The matching procedure is described in appendix A.1.

received from other patents, and the name and address of assignees.[10] PatentsView also provides citation level data that identifies the individual patents cited in each patent application. I link the LBD-BvD-USPTO data with Compustat to track the publicly listed status of firms in the sample.[11] S&P's Compustat derives from quarterly and annual financial reports filed by publicly listed companies. Several recent papers (Farre-Mensa and Ljungqvist (2016) and Dinlersoz et al. (2018)) find that listed firms are less financially constrained than privates ones. I therefore use a firm's publicly listed status to proxy for access to finance.

The linked data contain both patenting and non-patenting firms. The full data span 2007 through 2013 and contain information on approximately 91,000 U.S. firms and 92,000 owners. There are more owners than firms because some firms are jointly owned. The full data contain approximately 174,000 observations at the firm-owner-year level that account for about 25% of U.S. employment, 30% of payroll and 35% of revenue. I focus on patenting firms in the LBD-BvD-USPTO-Compusat linked data, of which there are about 10,000 unique firms, 80% of which are privately held. The analysis sample contains a total of 38,000 firm-owner-year observations between 2007 and 2013. Approximately 28,000 of these observations belong to firms held by corporate owners, 6,500 by individual owners, and 3,500 by institutional owners. Eighty percent of these observations are linked using either the EIN or the firm's name and full address information[12].

[10]These data were linked to LBD using name and address matching by Nikolas Zolas.

[11]The bridge between LBD and Compustat for 2002-2013 was created as part of Dinlersoz et al. (2018).

[12]The linking procedure entails 10 matching criteria. The first three criteria provide the highest quality matches. These criteria are 1) EIN, 2) firm name, street address, and zip code, and 3) firm name, city, state and zip code. 80% of analysis sample matches are made using one of these three.

1.3.2 Addressing selection

These 38,000 firm-owner-year observations constitute a sub-sample of patenting firms in the United States. Table 1.1 shows that firms in the analysis sample are large and old, with average employment above 9,000 and an average age of nearly 30. They have a patent stock exceeding 900 patents. They are held by quite diversified owners, who on average hold over 100 firms in their portfolio. And on average, ultimate owners control nearly 75% of a firm's equity. The average firm in the sample is therefore closely-held by a well-diversified owner. From the summary statistics alone, it is apparent that the raw sample is likely not representative.

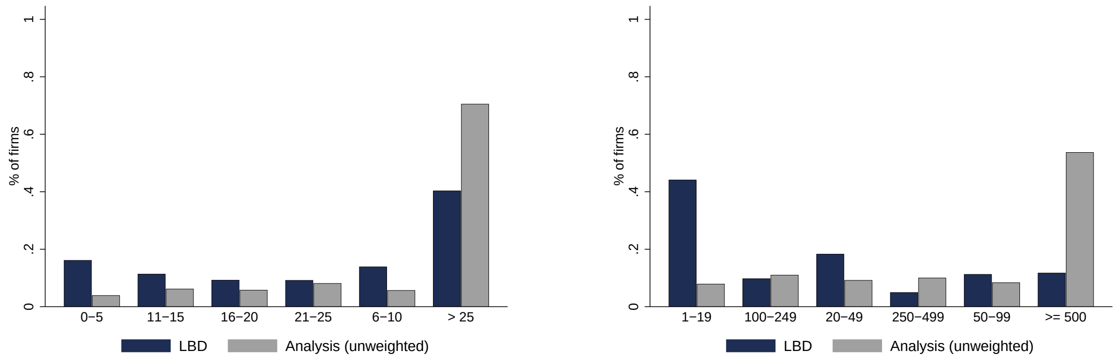
Table 1.1: Summary statistics (raw analysis sample)

	Mean	Stdev
employment	9,461	39,310
age	29.26	9.588
revenue growth	-0.0056	0.3623
employment growth	0.0062	0.2562
patent stock	962	6,582
diversification	103.3	345.3
concentration	0.7482	0.2518

Notes: The mean (column 1) and standard deviation (column 2) are reported. Data on employment, age, revenue growth and employment growth derive from the LBD. Revenue and employment growth are measured using DHS growth rates $\left(RG_{it} = \frac{RG_{it} - RG_{it-1}}{0.5(RG_{it} + RG_{it-1})}\right)$ for firm i in year t. Patent stock is obtained from PatentsView, and diversification (total number of firms held globally by an owner in a given year) and concentration (fraction of a firm's equity controlled by an owner) are obtained from BvD.

To further explore this issue, figure 1.1 plots the firm age and size distribution of patenting firms in the LBD and analysis sample. The x-axis of the left figure contains age bins ranging from $0-5$ to >25. The blue bar represents the fraction of patenting firms in the LBD in each age bin, and the grey bar represents the fraction of firms in the analysis sample in each age bin. In the right figure instead of age, the x-axis contains employment bins ranging from $1-19$ employees to ≥ 500 employees. Figure 1.1 shows that the analysis sample overrepresents the oldest and largest firms. The sample is also not representative along other dimensions, including employment growth and industry composition. Non-representativeness points to sample selection, which is a concern if the strength of the relationship between diversification and risky innovation varies systematically with these observables. Without addressing sample selection, I cannot ascertain the importance of diversification for risky innovation for the average patenting firm in the U.S. economy, or make inferences about the aggregate implications of the firm-level relationship.

Figure 1.1: Firm Age (left panel) and Employment (right panel) Distributions



Notes: The left figure plots firm age bins (ranging from 0-15 to ¿ 25) on the x-axis. The right figure plots firm employment bins (ranging from 1-19 employees to $\geq$ 500 employees. The height of each bar is the fraction of firms that belong to each bin. The blue bar represents the full sample of patenting firms in the LBD. The grey bar represents the sample of firms in my LBD-BvD-USPTO-Compustat linked data.

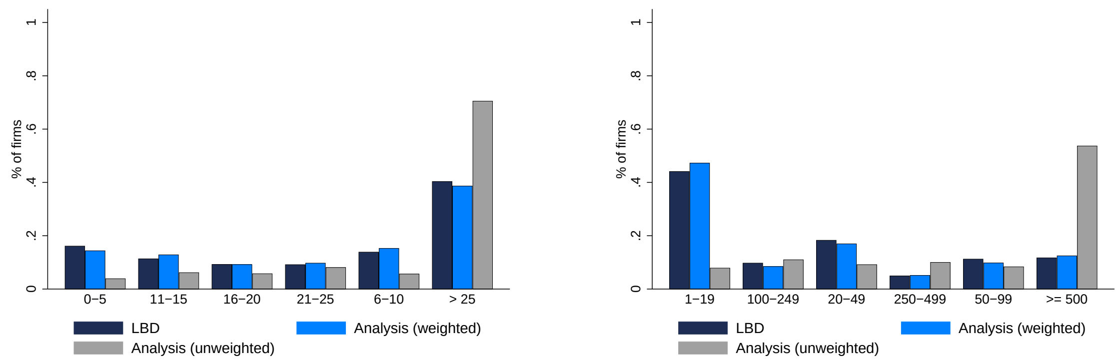
An advantage of linking ownership and patenting data to the LBD is that I can address sample selection directly. I focus on all patenting firms in the LBD and create an indicator variable equal to one if the firm (indexed by i) is also in the analysis sample. This indicator variable is the dependent variable of a logistic regression that controls for firm size ($\ln(emp_i)$), firm age (age_i), employment growth rate (EG_i), sector (γ_s), and an indicator for the oldest firms that is equal to one if the firm is 16 years or older ($DA16$):

$$O_i = \alpha + \beta_1 \ln(emp_i) + \beta_1 age_i + \beta_3 DA16_i + \beta_4 EG_i + \gamma_s + \varepsilon_{it} \tag{1.1}$$

Because firms in the data enter and exit the sample throughout the period, the logistic regression is run separately for each year. I use the inverse of the propensity scores from the regression to re-weight the data in subsequent analysis.

Figure 1.2, adds a bar to the the firm age and size distributions shown in figure 1.1. The light blue bars in the left and right panels of figure 1.2 represent the reweighted analysis data. After applying the propensity weights, the distributions of both firm age and size are near the distributions observed for patenting firms in the LBD. By using propensity weights in subsequent analysis, I can make statements about the relationship between risky innovation and owner diversification for the average patenting firm in the economy, and ascertain whether the firm-level relationship has aggregate implications.

Figure 1.2: Firm Age (left panel) and Employment (right panel) Distributions



Notes: The left figure plots firm age bins (ranging from 0-15 to ¿ 25) on the x-axis. The right figure plots firm employment bins (ranging from 1-19 employees to $\geq$ 500 employees. The height of each bar is the fraction of firms that belong to each bin. The blue bar represents the full sample of patenting firms in the LBD. The grey bar represents the sample of firms in my LBD-BvD-USPTO-Compustat linked data. The light blue bar represents the weighted LBD-BvD-USPTO-Compustat analysis sample. The weights are the inverse of the propensity weights from the logistic regressions discussed in the text.

1.3.3 Variable construction

Several variables are directly derived from the LBD, PatentsView, and Compustat. From the LBD, I obtain firm-level employment, revenue, age, and industry. Using PatentsView, I measure the patent stock (*stock*) of a firm in a particular year as the total number of patents it has been granted up to that point. With Compustat, I identify firms that are publicly listed, and use their listed status (*listed*) to proxy for access to finance. In addition to these variables, I construct variables measuring key features of ownership structure using Moody's BvD and risky innovation using PatentsView.

1.3.3.1 Ownership variables

Using Moody's BvD, I measure four distinct features of a firm's ownership structure – foreign ownership, owner type, ownership concentration, and owner diversification. For each firm in each year, I first identify the global ultimate owner (GUO). The GUO is the domestic or foreign owner holding the largest equity share in a firm. When BvD identifies multiple global ultimate owners for the same firm in a year, I keep the owners who have between 40% and 60% equity stake in the firm and track their characteristics separately. When this occurs, one firm will be associated with multiple owners in a particular year. BvD assigns each owner a unique, time-invariant identifier, the first two digits of which identify the owner's country. Using this information, I construct a discrete variable equal to one if the owner is located outside of the U.S. ($foreign$). Controlling for foreign ownership is important because foreign owners may have a preference for innovating in their domestic market and are subject to foreign aggregate or sectoral shocks that will not be absorbed in the industry-year fixed effects.

Several types of owners appear in the BvD ownership data, including individuals, industrial companies, banks, mutual funds, pension funds, and others. The reason ownership is not always traced down to the individual is that data are collected from official filings. In these filings if an investor sets up a holding company, her name does not appear as the owner of the individual firms in her portfolio. I group owner types into two broad categories – individual and company. The company category can be further broken down into industrial company and institutional investor. These owner types are differentially exposed to firm-specific risk. Individual owners listed in official documents are most exposed. Industrial companies provide limited liability to their owners, which reduces their exposure to risk. Institutional investors manage portfolios on behalf of investors and are therefore are least exposed to risk.

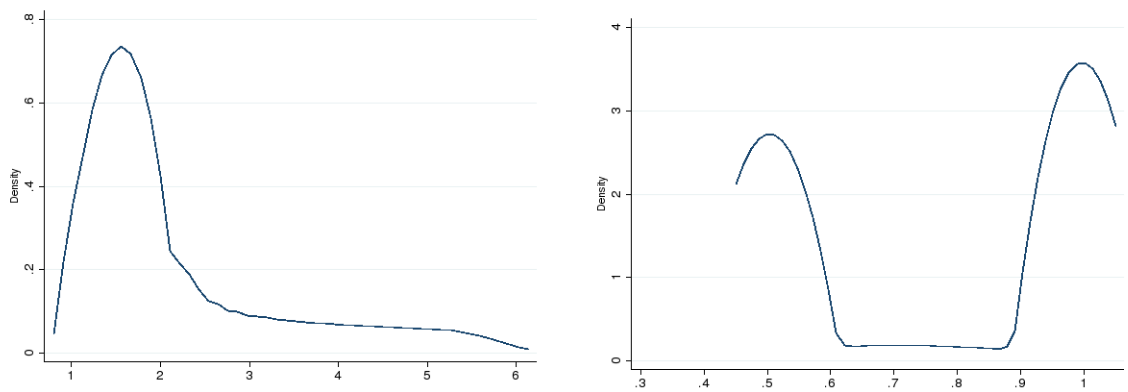
For each owner, I construct a measure of owner diversification in each year. For each owner-firm pair, I construct a measure of ownership concentration in each year. Although these measures are often conflated in the literature, they are both conceptually and empirically distinct.[13] It is therefore important to measure them separately. Owner diversification is measured as the total number of firms an owner controls globally in a particular year. Global holdings are measured using data from over 150 countries covered by BvD. If the owner holds only one firm, then he is undiversified relative to an owner holding 100 firms. Ownership concentration measures the percent of equity held by the ultimate owner in a particular firm. If the GUO controls 100% of equity, then the firm is closely held. If instead the GUO controls only 33%, then ownership is more dispersed since the remaining 67% of

[13]In the analysis sample, the correlation between diversification and concentration is only -0.03.

equity must be spread across other owners who each control less than 33% of equity.

The distributions of owner diversification and ownership concentration are shown in figure 1.3.[14] The left panel shows that the distribution of log owner diversification is very skewed and concentrated at low levels. The peak of the owner diversification distribution corresponds to an owner holding between five and six firms. Yet, some owners in the data hold over a hundred firms in their portfolio. In the right panel, ownership concentration is bimodal. Many firms are jointly owned and many firms are closely held.

Figure 1.3: Diversification (left panel) and Concentration (right panel) Kernel Density Plot



Notes: The left figure plots the kernel density function of log owner diversification, measured as the total number of firms held globally by an owner in a particular year. The right figure plots the kernel density function of ownership concentration, measured as the fraction of equity held by a firm's global ultimate owner. The left and right tails of the distributions have been trimmed for disclosure purposes. These figures pertain to the full BvD sample, rather than the patenting sample alone. This was done for disclosure purposes.

[14] Note that the figures are for the full data, not just the patenting sub-sample. This was done to facilitate disclosure and because these figures primarily serve an illustrative purpose.

1.3.3.2 Risky innovation

The patent-based measure of risky innovation used in this paper coincides closely with the finance and management literatures' notion of risky investment. In these literature, engaging in activities outside a firm's core business is considered risky because these types of investments are associated with higher and more uncertain returns. Following Akcigit et al. (2016), I define risky innovation as the technological propinquity between an individual patent and a firm's patent portfolio, and validate this measure by verifying that it is positively correlated with growth and volatility.

The measure is constructed in two stages. In the first stage, I use the citation-level data to calculate technological distance between any two patent classes (X and Y) as 1 minus the number of patents that cite both X and Y over the number of patents that cite either X or Y ($d^T(X,Y) = 1 - \frac{\#(X \cap Y)}{\#(X \cup Y)}$). Each patent is assigned an International Patent Classification (IPC) code. The IPC is a hierarchical system that classifies patents based on the technology areas to which they pertain. One technology area is Human Necessities, under which there are several 3-digit classes, including Agriculture (A01), Baking (A21), and Footware (A43). Consider a hypothetical example in which the technological distance between A01 and A43 is calculated. The number patents that cite either A01 and A43 is determined, as well as the number of these patents that cite both A01 and A43. In this hypothetical example, if the first is 100 and the second 10, then $d^T(A01, A43) = 1 - \frac{10}{100} = 0.90$.

In the second stage, I calculate the average distance between each new patent

p and firm $f's$ patent portfolio: $d^P(p,f) = \frac{1}{||P_f||}\sum_{p' \epsilon P_f}(X_p, Y_{p'})$. Suppose there is a firm that currently holds 10 patents, all of which belong in Computing (G06). Today, that firm applies for two patents, one in Computing (G06) and another in Aviation (B64). Suppose that $d^T(G06, B64) = 1$. The distance between the first patent in G06 and the firm's patent portfolio is zero, and the distance between the second patent in B64 and the portfolio is one. The measure of risky innovation at the firm-year level is the sum of the distances ($d^P(p,f)$) calculated for each new patent p, filed by firm f in a particular year. In the example above, the unadjusted number of new patents is two, but the risk-weighted patent count (RWP) is only one. To take into account that innovation is slow moving, I consider the past three years of firm patenting in calculating the risk-weighted patent count for a particular year.

The assumption underlying the risk-weighted patent count is that innovating outside of their existing areas of technological expertise is risky for firms. Instead, this type of patenting could be part of a firm's diversification strategy. To validate the underlying assumption and rule out the diversification story, I test whether thee risk-weighted patent count is positively associated with growth and volatility. If the diversification story were true, risk-weighted patent count and volatility would be negatively related.

I first measure firm-level growth and volatility. The DHS revenue growth rate is defined as $RG_{it} = \frac{R_{it} - R_{it-1}}{0.5(R_{it} + R_{it+1})}$. Following Kalemli-Ozcan et al. (2014), revenue growth volatility (VOL_{it}) is measured using a regression-based framework. The following regression is estimated:

$$RG_{it} = \phi_i + \gamma_{st} + \nu_{it} \tag{1.2}$$

where ϕ_i is firm fixed effects and γ_{st} is industry-year fixed effects. Revenue growth volatility (VOL_{it}) is calculated as ν_{it}^2, which captures how much revenue growth differs from the average growth (across all firms) in a particular sector and year st, and from average growth (over time) for a particular firm i. I then estimate the following regression:

$$\begin{aligned} Y_{it} = &\alpha + \phi_1 \log(RWP_{it-1}) + \beta_1 \log(stock_{it-1}) + \beta_2 \log(age_{it-1}) + \\ &\beta_3 \log(reveneue_{it-1}) + \beta_4 PUBLIC_{it} + \gamma_{st} + \varepsilon_{it} \end{aligned} \tag{1.3}$$

where Y_{it} stands in for the dependent variable. In particular, equation 1.3 regresses revenue growth rate (RG_{it}) and revenue growth volatility ($\log(VOL_{it}$) of firm i in period t on lagged risk-weighted patenting ($\log(RWP_{it-1})$), lagged patent stock ($\log(stock_{it-1})$), lagged firm age ($\log(age_{it-1})$), lagged firm revenue ($\log(reveneue_{it-1})$), a dummy variable indicating whether the firm is publicly listed ($PUBLIC_{it}$), and 4-digit industry-year fixed effects.

The first column of table 1.2 report the results for revenue growth and second column for revenue growth volatility. The results verify that risk-weighted patent count satisfies the criteria for risky investment since it is positively associated with both growth and volatility.

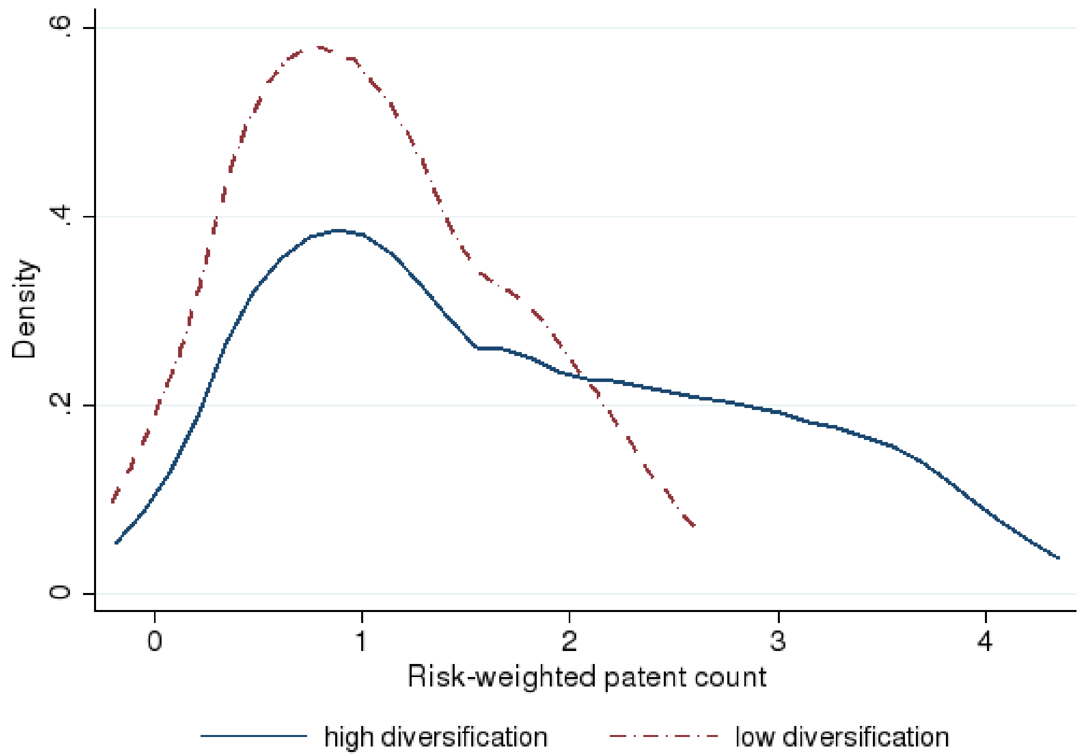
Table 1.2: Risky innovation, revenue growth and revenue growth volatility

	(1) RG	(2) VOL
$\log(RWP_{it-1})$	0.0568***	0.0174***
	(0.0025)	(0.0014)
$\log(stock_{it-1})$	0.0035***	0.0151***
	(0.0009)	(0.0007)
$\log(age_{it-1})$	-0.1389***	-0.0604***
	(0.0029)	(0.0030)
$\log(revenue_{it-1})$	-0.0675***	-0.0546***
	(0.0021)	(0.0013)
industry-year FE	Y	Y
listed status	Y	Y
obs.	196,000	194,000
R2	0.1946	0.2114

Notes: The first column report results for revenue growth (RG_{it}) and the second column report results for revenue growth volatility ($\log(VOL_{it})$). All controls are lagged by one period. These controls include risk-weighted (RWP), patent stock ($stock$), firm age (age), firm revenue ($revenue$), publicly listed status, left censored dummy, and 4-digit industry × year fixed effects. Standard errors clustered at the 4-digit industry × year level. se in parentheses [*** (1%), ** (5%), and * (10%)].

Before moving to more formal analysis, it is useful to evaluate the simple bivariate relationship between risky innovation and owner diversification. In Figure 1.4, firms are separated into those held by owners with high (solid line) and low (dashed line) levels of diversification and the distribution of log RWP is plotted for each type. The differences in risky innovation are striking. Firms held by more diversified owners engage in far riskier patenting than firms held by less diversified owners. Section 1.4 test whether the positive relationship between owner diversification and risky innovation holds under more formal analysis.

Figure 1.4: Risky Innovation and Diversification



Notes: The left panel plots the kernel density function of log risk-weighted patenting separately for firms held by owners with high diversification (solid blue line) and low diversification (dotted red line). The right panel plots the kernel density function of log risk-weighted patenting separately for firms held by owners with high ownership concentration (solid blue line) and low ownership concentration (dotted red line). Both tails of the distributions have been trimmed for disclosure purposes.

1.3.3.3 Descriptive statistics

The summary statistics of key firm-level variables are reported in table 1.3. The first two columns report raw means and standard deviations and the last two columns report the summary statistics using sampling weights. The average employment of the weighted sample is above 1,500 employees and the average firm age is 21 years. These statistics reflect that patenting firms tend to be older and larger than non-patenting firms in the economy, which is consistent with the findings of Graham et al. (2015). The average patent stock is nearly 200 patents and the average number of risk-weighted patents is three, but the large standard deviations associated with both variables indicate a high degree of variation across firms. The average degree of diversification is large, with an owner holding around 76 firms, but as the left panel of figure 1.3 shows, the distribution of diversification is very skewed.

Table 1.3: Summary statistics (raw analysis sample)

	Unweighted		Weighted	
	Mean	Stdev	Mean	Stdev
employment	9461	39310	1655	15710
age	29.26	9.588	20.64	12.2
revenue growth	-0.0056	0.3623	0.0075	0.6466
employment growth	0.0062	0.2562	0.05	0.494
patent stock	962	6582	187.2	2651
risk-weighted patenting	11.54	89.4	2.625	36.16
diversification	103.3	345.3	75.67	267.3
concentration	0.7482	0.2518	0.7702	0.2586

Notes: Columns 1 & 2 report the raw statistics and columns 3 & 4 report weighted statistics. Data on employment, age, revenue growth and employment growth derive from the LBD. Revenue and employment growth are measured using DHS growth rates $\left(RG_{it} = \frac{RG_{it}-RG_{it-1}}{0.5(RG_{it}+RG_{it-1})}\right)$. Patent stock is obtained from PatentsView, and diversification (total number of firms held globally by an owner in a given year) and concentration (fraction of a firm's equity controlled by an owner) are obtained from BvD.

1.3.3.4 Sector-level variables

For the sector-level analysis, I exploit variation across 2-digit NAICS codes over time. My measure of sector-level diversification (DIV_{st}) is the weighted average owner diversification of sector s in period t. More formally, $DIV_{st} = \Sigma_{ot}\,(diversification_{ot} \times weight_{ot})$, where $diversification_{ot}$ is the diversification of owner o that holds firms in sector s in year t; and $weight_{ot} = {}^{(\Sigma_{it}\, employment_{it} \times pw_{it})}/_{EMP_{st}}$, where $employment_{it}$ is the employment of firms held by owner o in period t, pw_{it} is their propensity weight, and EMP_{st} is total propensity weighted employment of sector s in period t.

I correlate sector-level diversification with several sector-level outcome variables. The first is weighted average risky patenting (RWP_{st}), which is measured as $ARWP_{st} = \Sigma_{it}(RWP_{it} \times weight_{it})$, where RWP_{it} is the risk-weighted patent count of firm i in sector s in period t, and $weight_{it} = {}^{(employment_{it} \times pw_{it})}/_{EMP_{st}}$. The second is total risky patenting ($TRWP_{st}$), which is calculated as the sum of risk-weighted patent count across all firms i in a sector s in period t. More formally, $TRWP_{st} = \Sigma_{it}\, RWI_{it}$. The third is total revenue, which is calculated as the sum of revenue across all firms i in a sector s in period t. Formally, $Trevenue_{st} = \Sigma_{it}\, revenue_{it}$. The final outcome variable is organic revenue growth, which is measured as $RG_{st} = \Sigma_{it}\,(RG_{it} \times weight_{it})$.

1.4 Empirical Analysis

I begin by evaluating the firm-level relationship between owner diversification and risky innovation. I then examine whether there is evidence of the risk-sharing channel, and explore whether the firm-level relationship has implications for sector-level outcomes.

1.4.1 Baseline results

I now turn to the central question of the paper, do firms held by more diversified owners engage in riskier innovation? The baseline specification estimates:

$$\begin{aligned}\log(RWP_{iot}) = &\alpha + \lambda_1 \log(diversification_{ot}) + \lambda_2 concentration_{iot} + \\ &\gamma_1 \log(employment_{it}) + \gamma_2 \log(age_{it}) + \gamma_3 \log(stock_{it}) + \gamma_4 \log(past_i) + \\ &\gamma_5 listed_{it} + \gamma_6 foreign_o + \gamma_7 LC_i + \eta_{st} + \varepsilon_{iot}\end{aligned} \tag{1.4}$$

Each firm i is held by owner o in period t. The dependent variable in equation 1.4 is risk-weighted patenting ($\log(RWP_{it})$) and is measured at the firm-year level (it). The variable of interest is owner diversification ($\log(diversification_{ot})$ and is measured at the owner-year level (ot). Theory predicts that due to risk-sharing, the coefficient λ_1 should to be positive. The specification distinguishes diversification from two other features of ownership structure – foreign ownership ($foreign_o$), which is measured at the owner level, and ownership concentration ($concentration_{iot}$), which is measured at the firm-owner-year level. Depending on whether higher concentration lowers agency conflict or raises the private benefits of control, the coefficient λ_2 may be positive or negative. Controlling for foreign ownership accounts for potential differences in preferences of foreign investors and for shocks not absorbed in industry-year fixed effects.[15]

The specification controls for important time-varying firm characteristics that may be simultaneously correlated with risky patenting and owner diversification, including employment ($\log(employment_{it})$), age ($\log(age_{it})$, and patent stock ($\log(stock_{it})$.

[15]The coefficient on $foreign$ is suppressed from output.

The time-varying discrete variable ($listed_{it}$) denotes whether a firms is actively publicly listed and proxies for access to finance.[16]. The time-invariant dummy variable LC_i is included to control for left-censoring of the firm age variable.[17] The inclusion of industry-year fixed effect (η_{st}) controls for cross-sectoral variation in patenting and ownership structure.

A potential concern is that the cross-sectional relationship between risky innovation and diversification will be driven by the endogeneity of these variables. In particular, the inherent riskiness of a firm may determine the type of owner it is held by. To account for this possibility, I construct a time-invariant firm-level variable that captures the average riskiness of innovation during a firm's first five years of patenting ($\log(past_i)$). The variable proxies for underlying unobserved firm heterogeneity. It is constructed using USPTO patenting data dating back to 1976. I focus on the first five years of patenting because the firm dynamics literature has emphasized the importance of early firm characteristics in explaining subsequent outcomes (Schoar (2010), Hurst and Pugsley (2011), Guzman and Stern (2016), Choi (2017), and others).

Table 1.4 reports the results of the baseline specification. The first column shows that when introduced together and without sampling weights, owner diversification and ownership concentration are both positively associated with risky innovation. Consistent with the risk-sharing story, there is a significant positive

[16]Recent research finds evidence that listed firms are less financially constrained than private ones. See Farre-Mensa and Ljungqvist (2016) and Dinlersoz et al. (2018) for the U.S. and Faccio et al. (2011) for Europe.

[17]The LBD tracks firms from 1976 onward and firm age is calculated based on the year in which the firm's oldest establishment is first observed in the data. As a result, the firm age of the oldest firms is left-censored.

relationship between diversification and risky innovation. The positive relationship between concentration and risky innovation is consistent with higher concentration lowering agency frictions and incentivizing risk-taking. The positive coefficient on employment suggests that all things equal, larger firms have more resources and organizational capacity to undertake risky patenting. The positive coefficient on patent stock suggests that all things equal, firms with more patenting experience are better equipped to apply their existing expertise in new technological areas. The negative coefficient on age suggests that all things equal, younger firms are more dynamic and willing to undertake risky patenting. This last result is consistent with the insights of the firm dynamics literature that young firms are engines of growth and innovation.

Before introducing sampling weights in columns (3) through (7), I explore whether the relationship between diversification and risky innovation varies systematically across firm types. I start with the specification in column (1) and introduce interaction terms between owner diversification and ownership concentration and firm size and age. Recall that the unweighted analysis sample over-represents old and large firms. Sampling weights therefore assign relatively more weight to observations belonging to young and small firms. The results in column (2) indicate that reweighting towards younger firms is critical. Reweighting towards small firms strengthens the relationship between concentration and risky innovation and weakens it between diversification and risky innovation. Reweighting towards young firms weakens the relationship between concentration and risky innovation and strengthens it between diversification and risky innovation. The weighted version the specification in column (1) is reported in column (6). The result indicates that the latter effect (reweighting towards young firms) dominates the former effect (reweighting towards small firms). These results highlight the fact that sample selection bias matters, and that it is important to investigate the various dimensions along which a sample is not representative. In the remainder of the analysis, sampling weights are used to address sample selection bias.

Columns (3) through (7) introduce different control variables to highlight how their inclusion impacts the core relationship between diversification and risky innovation. All results in columns (3) through (7) include sampling weights and 4-digit industry-year fixed effects. Without controlling for any other ownership structure, firm lifecycle or financial structure variables, column (3) highlights the strong positive relationship between diversification and risky innovation. The inclusion of ownership concentration in column (4), which itself is negatively correlated with risky innovation, has little effect on the coefficient on diversification. This results from the low correlation (-0.03) between owner diversification and ownership concentration. The inclusion of firm age and employment in column (5) and patent stock, listed status, and foreign ownership in column (6) attenuates the relationship between diversification and risky innovation, though it remains positive and significant. This attenuation occurs because in the naive specifications that omit these controls, the relationship between these variables and risky innovation is attributed to diversification.

The result reported in column (7) serves as my baseline. This specification controls for ownership concentration, foreign ownership and time-varying firm characteristics, and it verifies that the significant positive coefficient on diversification is not driven by inherent firm heterogeneity by introducing a control for past risky patenting. Owner diversification remains positive and significant (and ownership concentration remains insignificant), but its effect is attenuated relative to column (6). The result confirms that inherent firm heterogeneity, particularly underlying risk profile, does influence ownership structure, but alone cannot fully explain the relationship between diversification and risky innovation. In this preferred baseline specification, a one standard deviation increase in owner diversification is associated with an approximately 5% increase in risky innovation.

1.4.2 First differences

The baseline specification corrects for sample selection bias and introduces a rich set of controls that go a long way in addressing selection on observables, but unobserved heterogeneity precludes a causal interpretation. In particular, the baseline specification controls for important time-varying firm characteristics (employment, age, patent stock, and access to finance), a time-varying firm-owner characteristic (ownership concentration), a time-invariant owner characteristic (foreign owner), and time-invariant firm characteristics (past risky patenting and left-censoring). Yet, controlling for a firm's past risky patenting does not account for all of the inherent firm characteristics that may influence risk-taking and make firms attractive to particular types of owners. Therefore, the positive relationship between diversification and risky patenting may still arise from more diversified owners acquiring

Table 1.4: Cross-sectional specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log(diversification_{ot})$	0.0222***	0.0161***	0.0763***	0.0761***	0.0538***	0.0406***	0.0284***
	(0.0047)	(0.0047)	(0.0106)	(0.0107)	(0.0109)	(0.0090)	(0.0070)
$\log(diversification_{ot}) \times \log(age_{it})$		-0.0221***					
		(0.0083)					
$\log(diversification_{ot}) \times \log(emp_{it})$		0.0228***					
		(0.0028)					
$concentration_{iot}$	0.0769**	0.0686**		-0.1427***	-0.0923*	0.0032	0.0021
	(0.0325)	(0.0326)		(0.0490)	(0.0473)	(0.0429)	(0.0379)
$concentration_{iot} \times \log(age_{it})$		0.0849					
		(0.0516)					
$concentration_{iot} \times \log(emp_{it})$		-0.0328					
		(0.0200)					
$\log(employment_{it})$	0.1394***	0.1421***			0.1382***	0.0774***	0.0721***
	(0.0055)	(0.0055)			(0.0078)	(0.0086)	(0.0084)
$\log(age_{it})$	-0.2698***	-0.2742***			-0.0561***	-0.1466***	-0.1024***
	(0.0146)	(0.0156)			(0.0217)	(0.0231)	(0.0199)
$\log(stock_{it})$	0.3304***	0.3276***				0.2062***	0.1075***
	(0.0055)	(0.0054)				(0.0166)	(0.0130)
$\log(past_{it})$							0.5014***
							(0.0514)
industry-year FE	Y	Y	Y	Y	Y	Y	Y
listed status	Y	Y	N	N	N	Y	Y
foreign ownership	Y	Y	N	N	N	Y	Y
DLC	Y	Y	N	N	Y	Y	Y
weights	N	N	Y	Y	Y	Y	Y
obs.	38,000	38,000	38,000	38,000	38,000	38,000	38,000
r-sq	0.5980	0.6011	0.1241	0.1259	0.2165	0.3905	0.4654

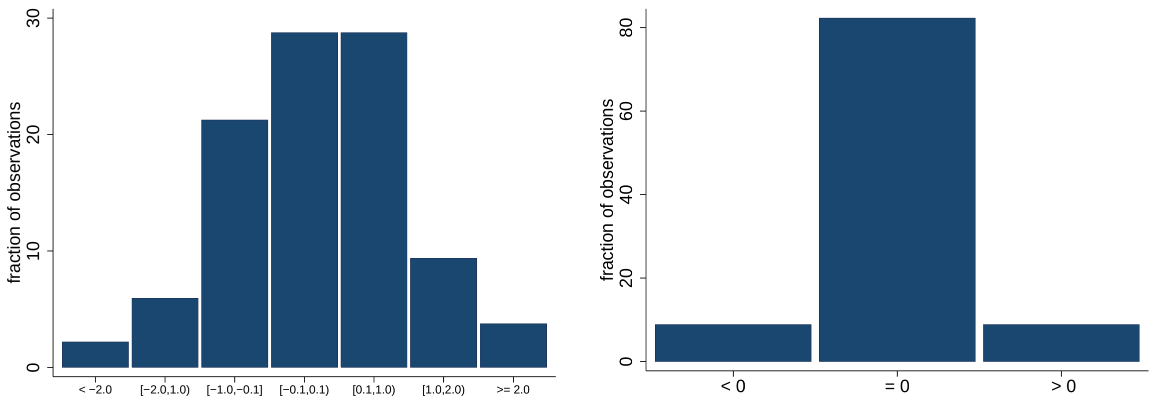
Notes: The dependent variable is risk-weighted patents. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, patent stock, past risk-taking, listed status, foreign ownership dummy, left-censored dummy, and 4-digit ind-year FE. Standard errors clustered at the owner-level. SE in parentheses [*** (1%), ** (5%), and * (10%)].

riskier firms, rather than incentivizing them to engage in riskier innovation. If the positive relationship was entirely driven by this story, then changes in owner diversification should not be associated with changes in firms' innovation behavior.

In the absence of an instrument or exogenous shock to ownership structure during the 2007 through 2013 period, I exploit within-firm variation to directly test whether changes in diversification and/or concentration are associated with changes in risky innovation. In particular, I exploit variation in risky patenting and ownership structure within firms over time using a first-difference specification. Because ownership structure evolves slowly, I focus on a sub-sample of firms observed for the majority of the sample period (5 years or more) to ensure I have sufficient variation in owner diversification and/or ownership concentration to make inference. As in the baseline specific it is important to control for ownership concentration to isolate the role of diversification.

Figure 1.5 documents the distribution of annual within-firm changes in diversification and concentration among firms observed for 5 years or more. In the left panel changes in diversification are categorized into seven bins and in the right right panel changes in concentration are categorized into three bins. The height of each bar is the fraction of observations that fall into each bin. The results indicate that owner diversification (left panel) is subject to more change than ownership concentration (right panel). While ownership concentration is extremely persistent, with over 80% of observations experiencing no change in this measure, ownership diversification is subject to more fluctuations. If changes in ownership structure are associated with changes in risky patenting, it is therefore more likely that diversification plays a role than concentration.

Figure 1.5: Δ Diversification (left panel) and Δ Concentration (right panel)



Notes: In the left panel, one-year changes in diversification at the firm level are categorized into seven bins depending on the degree of change (calculated as the change in log diversification between $t-1$ and t). In the right panel, one year changes in concentration at the firm level are categorized into three bins depending on the degree of change. The height of each column is the percent of observations that fall into each category.

For the sample of firms observed for the majority of the sample period, I estimate the following first difference regression:

$$\begin{aligned}\Delta_1 \log(RWP_{iot}) =& \lambda_1 \Delta_1 \log(diversification_{ot}) + \lambda_2 \Delta_1 concentration_{iot} + \\ & \gamma_1 \Delta_1 \log(employment_{it}) + \gamma_2 \Delta_1 \log(stock_{it}) + \\ & \gamma_5 \Delta_1 listed_{it} + \gamma_6 \Delta_1 foreign_o + \eta_{st} + \varepsilon_{iot}\end{aligned} \tag{1.5}$$

where Δ_1 denotes the change in a particular variable between year $t-1$ and t. Note that only time-varying firm, owner, and firm-owner characteristics are included in the specification. Since the first-difference specification controls for firm fixed-effects, firm age is dropped. Note further that $\Delta_1 foreign_o$ is included as a control because in this specification firms may experience changes in ownership over the period, which may involve being bought or sold to owners with a different foreign status.

Table 1.5 reports the results of this specification. The results in column (1) confirm the presence of a positive and significant relationship between changes in owner diversification and changes in risky patenting. These results control for time-invariant firm characteristics, and address the concern that owners are targeting firms with particular risk-profiles. If this were the case, firms would be unresponsive to changes in owner diversification because they would already be innovating at their underlying level of riskiness. Instead, it appears that firm innovation is sensitive to fluctuations in diversification.

This positive relationship may still be driven by unobserved owner characteristics. The firm dynamics literature emphasizes the importance of owner ability and prior experience for entrepreneurial activities. High ability owners may be better equipped to take advantage of both diversification and innovation opportunities. To address this concern, in column (2) of table 1.5, I further restrict the sample to only those firms held by the same owner over the whole period. In column (3) I also restrict the sample to a balanced sample of firms present in the data throughout the entire period to rule out concerns about firm entry/exit. In these specifications, changes in owner diversification arise from a firm's existing owner expanding or contracting her portfolio, after account for time-invariant owner characteristics.[18] I find that higher owner diversification incentivizes riskier innovation. Given the rich set of controls and focus on matched firm-owner pairs, these specifications lend themselves to a causal interpretation as long as owner diversification and the re-

[18]Note that since these specifications control for time invariant owner characteristics, $\Delta foreign_o$ is dropped from the regressions.

Table 1.5: First difference specification

	all	same	balanced
$\Delta_1 \log(diversification)$	0.0309***	0.0450***	0.0258**
	(0.0119)	(0.0152)	(0.0129)
$\Delta_1 concentration$	0.0046	0.0184	-0.0154
	(0.0591)	(0.0658)	(0.0755)
$\Delta_1 \log(employment)$	0.0164	0.0061	-0.0191
	(0.0301)	(0.0407)	(0.0395)
$\Delta_1 \log(stock)$	-0.0314	-0.0426	-0.0227
	(0.0298)	(0.0302)	(0.0489)
industry-year FE	Y	Y	Y
listed status	Y	Y	Y
weights	Y	Y	Y
obs.	16,000	10,000	7,000
r-sq	0.1444	0.1817	0.1869

Notes: In column 1 the sample consists of firms observed in the data for five years or more. Columns 2 and 3 further restrict the sample to firms held by the same owner over the whole period they are observed in the data. Column 3 further restricts the sample to a balanced panel of firms. All variables are measured in changes between year $t-1$ and t. The dependent variable is change in risk-weighted patents. The variable of interest is change in owner diversification. Controls include changes in ownership concentration, firm employment, patent stock, listed status, and foreign ownership dummy (column 1). 4-digit industry-year FE are included. Standard errors clustered at the owner level. SE in parentheses [*** (1%), ** (5%), and * (10%)].

maining unobserved firm and owner characteristics summarized in the error terms are orthogonal.

The previous specification accounts for time-varying firm characteristics and time-invariant firm and owner characteristics. However, an alternative story posits that the positive relationship arises not from increasing diversification incentivizing more risky innovation, but from more risky innovation incentivizing owners to become more diversified to offset the increased risk they face. When deciding whether to sell firms or acquire new ones, investors are not solely considering the riskiness of the patenting being undertaken in the firms they own. First, if the goal was to hedge risk arising from risky innovation, owners would likely first diversify their financial portfolio, which is less costly and time-consuming than opening a new firm or closing one down. Second, the decision to open a new firm, for example, is often heavily driven by the recognition of growth opportunities in a new market (location, industry, etc). To more formally address this story of reverse causality I perform an additional test. I focus on a balanced sample of firms to rule out the possibility that the results are driven by firm entry and exit and calculate changes in risky innovation and other time-vary firm-level controls between year $t-3$ and t. To prevent the dynamic feedback from riskier innovation leading to higher owner diversification, I measure owner diversification and ownership concentration at the beginning of the period:

$$\begin{aligned}\Delta_3 \log(RWP_{iot}) = &\lambda_1 \log(\textit{initial diversification}_o) + \lambda_2 \textit{initial concentration}_{io} + \\ &\gamma_1 \Delta_3 \log(\textit{employment}_{it}) + \gamma_2 \Delta_3 \log(\textit{stock}_{it}) + \\ &\gamma_5 \Delta_3 \textit{listed}_{it} + \eta_{st} + \varepsilon_{iot}\end{aligned} \tag{1.6}$$

where Δ_3 denotes the change in a particular variable between year $t-3$ and t. This initial conditions specification differences out time-invariant firm characteristics and controls for time-varying firm characteristics. It compares changes in risky innovation of firms held by initially more diversified owners with changes in risky innovation of firms held by initially less diversified owners. The first column of table 1.6 repeats the specification reported in column (3) of table 1.5 using changes between year $t-3$ and t rather than between year $t-1$ and t. It confirms the positive relationship between changes in owner diversification and changes in risky innovation. The second column of table 1.6 reports the results of the initial conditions specification. The results show that changes in risky innovation are higher among firms held by initially more diversified owners. This positive relationship between initial owner diversification and changes in risky innovation lends credence to the story that higher owner diversification incentivizes risky innovation as long as initial owner diversification and remaining time invariant owner and time varying firm characteristics are orthogonal.

The specifications exploiting within firm and within owner variation over time are complementary. While the first difference results show that the positive relationship between diversification and risky innovation is not driven by time invariant firm and owner characteristics, the initial conditions specification shows that the positive relationship is not entirely driven by the dynamic feedback from risky innovation to owner diversification. Compared to previous empirical studies, the detailed data and empirical approaches employed here make a causal interpretation of the relationship between owner diversification and risky innovation more plausible. Even with remaining questions regarding the identifying assumptions, I document a new finding that owner diversification facilitates risky innovation among patenting firms in the United States.

Table 1.6: Initial conditions specification

	(1)	(2)
$\Delta_3 \log(diversification)$	0.0272**	
	(0.0128)	
$\Delta_3 concentration$	0.0242	
	(0.0825)	
log(*int'l diversification*)		0.0199**
		(0.0094)
int'l concentration		-0.1842***
		(0.0657)
$\Delta_3 \log(employment)$	-0.0587	-0.0621
	(0.0395)	(0.0414)
$\Delta_3 \log(stock)$	-0.0821	-0.0845
	(0.0729)	(0.0747)
industry-year FE	Y	Y
listed status	Y	Y
weights	Y	Y
obs.	5,000	5,000
r-sq	0.0455	0.0444

Notes: The sample contains firms observed during the entire period and that are held by the same owner throughout. All variables in column (1) are measured as changes between year $t-3$ and t. In column (2) the ownership structure variables (ownership concentration and owner diversification) are measured at the beginning of the period. The dependent variable is change in risk-weighted patents. The variable of interest is change in owner diversification (column 1) or initial owner diversification (column 2). Controls include changes in ownership concentration (column 1) or initial ownership concentration (column 2) and changes in firm employment, patent stock, and listed status. 2-digit industry-year FE are included. Standard errors clustered at the owner level. SE in parentheses [*** (1%), ** (5%), and * (10%)].

1.4.3 Risk-sharing channel

In the theoretical literature, the risk-sharing channel arises from the exposure of risk-averse agents to idiosyncratic risk. To test whether there is evidence of this channel, I take advantage of the different types of owners present in the BvD data. In table 1.7, I estimate the baseline regression (column 3 of table 1.4) separately for corporate and individual owners. The first two columns report unweighted results and the last two report weighted results. First, the table confirms that risky innovation remains positively associated with owner diversification and unrelated to ownership concentration across owner types. More importantly, the relationship between diversification and risky patenting is stronger for individual than corporate owners. This result is consistent with the risk-sharing channel since individual owners in the data have not set up holding companies, and are therefore even more exposed to the risk of firms in their portfolio than corporate owners. Note that the results are also robust to decomposing the owner types into three groups – individual, corporate, and institutional owners. The positive relationship between diversification and risky innovation holds across owner types, but is only significant at the 10% level for institutional owners.[19] This result is also consistent with the risk-sharing channel since institutional investors manage holdings on behalf of individual investors and therefore have less stake and exposure to firms in the portfolio. Therefore, the theory of risk-sharing is least relevant for this type of owner.

[19] Note that the quantitative results for institutional investors are under disclosure review. Only the qualitative results for this type of owner has passed disclosure review at this time.

Table 1.7: Owner diversification & risky innovation across owner types

	Corporate	Individual	Corporate	Individual
log($diversification_{ot}$)	0.0231***	0.0409***	0.0322***	0.0351***
	(0.0033)	(0.0152)	(0.0056)	(0.0120)
$concentration_{iot}$	0.0138	-0.0205	-0.0056	0.0028
	(0.0271)	(0.0421)	(0.0395)	(0.0308)
log($employment_{it}$)	0.1297***	0.0695***	0.0685***	0.0480***
	(0.0071)	(0.0067)	(0.0066)	(0.0078)
log(age_{it})	-0.2326***	-0.1103***	-0.1071***	-0.0504***
	(0.0102)	(0.0170)	(0.0136)	(0.0115)
log($stock_{it}$)	0.2577***	0.1292***	0.1214***	0.0606***
	(0.0066)	(0.0152)	(0.0121)	(0.0090)
log($past_i$)	0.2702***	0.3616***	0.4848***	0.3843***
	(0.0162)	(0.0687)	(0.0503)	(0.0791)
industry-year FE	Y	Y	Y	Y
listed status	Y	Y	Y	Y
foreign ownership	Y	Y	Y	Y
weights	N	N	Y	Y
obs.	26,000	6,000	26,000	6,000
r-sq	0.5767	0.4564	0.4512	0.3449

Notes: The dependent variable is risk-weighted patents. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, patent stock, past risk-taking, listed status, foreign ownership dummy, left-censored dummy, and 3-digit industry-year FE. Standard errors clustered at the 3-digit industry × year level. se in parentheses [*** (1%), ** (5%), and * (10%)].

1.4.4 Robustness

The baseline results establish a positive and significant relationship between owner diversification and risky patenting when diversification is measured by the number of firms an owner holds globally. Table 1.8 tests whether the positive relationship persists when alternative definitions of owner diversification are considered. The first column serves as a reference point and reports the results from the baseline specification in column 3 of table 1.4. The second column measures diversification by the total number of firms controlled domestically (i.e. the number of firms in the LBD held by each owner). This definition recognizes that over three-fourths of U.S. firms' R&D expenditure is performed domestically (Shackelford and Wolfe (2011)) and therefore domestic holdings may be particularly relevant for innovation-related decisions. The third column measures diversification as the number of unique industries (3-digit NAICS codes) in which an owner holds firms. It recognizes that an owner holding three firms in apparel manufacturing (code 315) may not be as diversified as another owner holding three firms, in apparel manufacturing (315), chemical manufacturing (325), and animal production and aquaculture (112). The fourth column measures diversification as 1 minus an employment-based concentration index. It distinguishes between an owner holding three firms with 90% of employment in one of them, and an owner holding three firms with employment equally spread across them. The fifth column measures diversification as 1 minus an industry-level employment-based concentration index. The sixth column measures diversification as the negative of the owner's weighted industry-based beta. The measure is constructed by first estimating the industry-specific beta for 48 Fama-French industries using the Fama-French three factor model; then mapping these industries to 3-digit NAICS codes; and calculating the owner's weighted beta using the total employment of firms held by the owner in a particular industry divided by the total employment of all firms in the owner's portfolio as weights. This measure captures whether an owner is more diversified (lower beta) or less diversified (higher beta) than the market portfolio. Across all six definitions, owner diversification remains positively associated with risky innovation. Quantitatively, the results are also similar to the baseline. For instance, a one standard deviation increase the number of active 3-digit industries is associated with nearly a 5% increase in risky innovation.

One concern with the risk-weighted patent count (RWP) is that it does not account for firms engaging in defensive patenting. Firms could patent outside their area of expertise without intending to implement the new technologies to hinder other firms from entering those markets. I construct a quality-adjusted risk-weighted patent count measure (RWC) that gives more weight to patents that are cited by other patents. Patent citations are a commonly used proxy for patent quality (Aghion et al. (2013), Akcigit et al. (2016)). If risky patents are defensive, then they should garner few subsequent citations. Table 1.9 tests the relationship between quality-adjusted patent count and the six alternative measures of owner diversification. The results confirm that the baseline relationship is not driven by defensive patenting since the positive relationship persists and remains significant across all six specifications. In fact, the relationship is strengthened. A one standard

Table 1.8: Alternative definitions of diversification

	(1)	(2)	(3)	(4)	(5)	(6)
log(diversification$_{ot}$)	0.0263***					
	(0.0050)					
log(# firms owned (LBD)$_{ot}$)		0.0490***				
		(0.0123)				
log(# active ind$_{ot}$)			0.0651***			
			(0.0151)			
1-HHI (emp)$_{ot}$				0.1144**		
				(0.0523)		
1-HHI (ind)$_{ot}$					0.1519**	
					(0.0609)	
-(weighted ind. β)$_{ot}$						0.1268**
						(0.0566)
concentration$_{iot}$	0.0100	0.0071	0.0067	-0.0021	-0.0028	0.0110
	(0.0294)	(0.0296)	(0.0298)	(0.0297)	(0.0298)	(0.0282)
log($employment_{it}$)	0.0814***	0.0829***	0.0828***	0.0837***	0.0835***	0.0806***
	(0.0074)	(0.0072)	(0.0071)	(0.0073)	(0.0072)	(0.0068)
log(age_{it})	-0.1138***	-0.1142***	-0.1138***	-0.1152***	-0.1148***	-0.1101***
	(0.0132)	(0.0131)	(0.0130)	(0.0130)	(0.0129)	(0.0131)
log($stock_{it}$)	0.1225***	0.1244***	0.1242***	0.1244***	0.1245***	0.1273***
	(0.0101)	(0.0101)	(0.0101)	(0.0102)	(0.0102)	(0.0098)
log($past_i$)	0.4773***	0.4772***	0.4764***	0.4815***	0.4808***	0.4903***
	(0.0340)	(0.0335)	(0.0333)	(0.0341)	(0.0339)	(0.0350)
industry-year FE	Y	Y	Y	Y	Y	Y
listed	Y	Y	Y	Y	Y	Y
foreign	Y	Y	Y	Y	Y	Y
weights	Y	Y	Y	Y	Y	Y
obs.	38,000	38,000	38,000	38,000	38,000	37,000
r-sq	0.5045	0.5039	0.5042	0.5029	0.5031	0.5069

Notes: The dependent variable is risk-weighted patents. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, patent stock, past risk-taking, listed status, foreign ownership dummy, left-censored dummy, and 4-digit industry-year FE. Owner diversification is measured as total number of firms held globally (column 1), number of domestic firms (2), number of unique active 3-digit industries (3), one minus an employment concentration index (4), one minus an industry-based employment concentration index (5), negative of the owner's weighted industry-based beta (6). S.E. clustered at the 4-digit industry × year level. SE in parentheses [*** (1%), ** (5%), and * (10%)].

deviation increase in the baseline measure of diversification is associated with nearly an 8% increase in quality-adjusted risky patenting; and a one standard deviation increase in the number of active 3-digit industries is associated with a 7% increase in quality-adjusted risky patenting.

Another possibility is that the risk-weighted patent count is capturing firms innovating outside of their own area of expertise, but within their owner's area of expertise. If this were the case, then the distance between a firm's new patents and its owner's patent portfolio would be smaller than the distance between a firm's new patents and its own patent portfolio. In particular, since more diversified owners are active in more technological areas, the patenting of firms in their portfolio would appear less risky under the owner-based measure than the firm-based measure. If this story is true, then I would expect the positive relationship between diversification and risky innovation to be attenuated when the dependent variable is calculated as the technological distance between a firm's new patents and its *owner's* patent portfolio (owner-based risk-weighted patent count). Table 1.10 shows that instead of weakening the results, the positive relationship between diversification and owner-based risky innovation is stronger than the relationship between diversification and firm-based risky innovation. A one standard deviation increase in the baseline measure of diversification is associated with nearly an 8% increase in owner-based risky innovation; and a one standard deviation increase in the number of active 3-digit industries is associated with a 7% increase in owner-based risky innovation.

Innovation is not the only means by which firms engage in risky investment. For example, expansion into new industries is potentially risky because it entails

Table 1.9: Quality-adjusted risk-weighted patenting

	(1)	(2)	(3)	(4)	(5)	(6)
log(diversification$_{ot}$)	0.0415***					
	(0.0072)					
log(# firms owned (LBD)$_{ot}$)		0.0802***				
		(0.0186)				
log($\#activeind_{ot}$)			0.1086***			
			(0.0227)			
1-HHI (emp)$_{ot}$				0.1800**		
				(0.0739)		
1-HHI (ind)$_{ot}$					0.2370***	
					(0.0859)	
-(weighted ind. β)$_{ot}$						0.2626***
						(0.0836)
concentration$_{iot}$	0.0165	0.0128	0.0125	-0.0026	-0.0038	0.0130
	(0.0429)	(0.0432)	(0.0434)	(0.0435)	(0.0437)	(0.0415)
log($employment_{it}$)	0.1175***	0.1198***	0.1195***	0.1212***	0.1209***	0.1174***
	(0.0106)	(0.0103)	(0.0103)	(0.0105)	(0.0104)	(0.0098)
log(age_{it})	-0.1774***	-0.1779***	-0.1771***	-0.1798***	-0.1792***	-0.1761***
	(0.0155)	(0.0153)	(0.0153)	(0.0153)	(0.0152)	(0.0159)
log($stock_{it}$)	0.2109***	0.2139***	0.2133***	0.2142***	0.2142***	0.2178***
	(0.0146)	(0.0147)	(0.0146)	(0.0148)	(0.0148)	(0.0149)
log($past_i$)	0.3432***	0.3425***	0.3420***	0.3466***	0.3462***	0.3557***
	(0.0236)	(0.0231)	(0.0231)	(0.0237)	(0.0239)	(0.0246)
industry-year FE	Y	Y	Y	Y	Y	Y
listed	Y	Y	Y	Y	Y	Y
foreign	Y	Y	Y	Y	Y	Y
weights	Y	Y	Y	Y	Y	Y
obs.	38,000	38,000	38,000	38,000	38,000	37,000
r-sq	0.4724	0.4718	0.4723	0.4702	0.4705	0.4737

Notes: The dependent variable is quality adjusted risk-weighted patents. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, patent stock, past risk-taking, listed status, foreign ownership dummy, left-censored dummy, and 4-digit industry-year FE. Owner diversification is measured as total number of firms held globally (column 1), number of domestic firms (2), number of unique active 3-digit industries (3), one minus an employment concentration index (4), one minus an industry-based employment concentration index (5), negative of the owner's weighted industry-level beta (6). S.E. clustered at the 4-digit industry × year level. SE in parentheses [*** (1%), ** (5%), and * (10%)].

Table 1.10: Owner-based risk-weighted patent count

	(1)	(2)	(3)	(4)	(5)	(6)
log(diversification$_{ot}$)	0.0409***					
	(0.0051)					
log(# firms owned (LBD)$_{ot}$)		0.0841***				
		(0.0124)				
log(# active ind$_{ot}$)			0.1076***			
			(0.0152)			
1-HHI (emp)$_{ot}$				0.2048***		
				(0.0545)		
1-HHI (ind)$_{ot}$					0.2546***	
					(0.0635)	
-(weighted β)$_{ot}$						0.1818***
						(0.0603)
concentration$_{it}$	0.0133	0.0098	0.0082	-0.0055	-0.0073	-0.0108
	(0.0296)	(0.0301)	(0.0302)	(0.0298)	(0.0300)	(0.0293)
[1em] log($employment_{it}$)	0.0805***	0.0827***	0.0828***	0.0838***	0.0837***	0.0860***
	(0.0071)	(0.0070)	(0.0070)	(0.0071)	(0.0071)	(0.0069)
log(age_{it})	-0.1224***	-0.1232***	-0.1226***	-0.1246***	-0.1240***	-0.1252***
	(0.0140)	(0.0138)	(0.0138)	(0.0139)	(0.0137)	(0.0141)
log($stock_{it}$)	0.1191***	0.1214***	0.1210***	0.1217***	0.1217***	0.1225***
	(0.0103)	(0.0104)	(0.0103)	(0.0105)	(0.0104)	(0.0105)
log($past_{it}$)	0.4937***	0.4934***	0.4924***	0.5003***	0.4992***	0.5030***
	(0.0365)	(0.0361)	(0.0358)	(0.0369)	(0.0365)	(0.0377)
industry-year FE	Y	Y	Y	Y	Y	Y
weights	Y	Y	Y	Y	Y	Y
obs.	37,000	37,000	37,000	37,000	37,000	37,000
r-sq	0.5015	0.5008	0.5013	0.4981	0.4985	0.4968

Notes: The dependent variable is owner-based risk weighted patent count. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, patent stock, past risk-taking, listed status, foreign ownership dummy, left-censored dummy, and 4-digit industry-year FE. Owner diversification is measured as total number of firms held globally (column 1), number of domestic firms (2), number of unique active 3-digit industries (3), one minus an employment concentration index (4), one minus an industry-based employment concentration index (5), negative of the owner's weighted industry-level beta (6). S.E. clustered at the 4-digit industry × year level. se in parentheses [*** (1%), ** (5%), and * (10%)].

firms entering new markets, facing new competitors, attracting new customers, and incurring disruptions during the expansion. Expansion into new industries may be particularly relevant for patenting firms because a potential reason for these firms to engage in risky innovation is the desire to enter new markets. In table 1.11, I test whether firms held by more diversified owners also undertake risky investments outside of patenting by asking whether they are more likely to expand into new industries. I construct a measure of industry expansion using information on establishment openings from the LBD. The dependent variable is a discrete variable equal to one if a firm has opened an establishment in a new 3-digit industry over the previous three years. The regression controls for the stock of active industries ($\log(stock_{it})$), measured by the number of unique 3-digit industries in which the firm is active; and in the last column also controls for the amount of industry-expansion the firm undertook in its first five years of operation ($past_{it}$). Consistent with the risky innovation results, table 1.11 shows a positive relationship between owner diversification and industry expansion. As with previous results, ownership concentration has no significant effect on industry expansion, now in both unweighted (column 1) and weighted (columns 2 and 3) regressions.[20] The results suggest that firms held by more diversified owners engage in risky investments broadly, though I focus in this paper on their innovation strategies specifically.

[20] Firm expansion into new industries can also be seen as an independent form of risky investment. A robustness exercise that expands the sample of firms to non-patenting firms confirms the positive relationship between diversification and industry expansion in the broader sample.

Table 1.11: Industry expansion

	(1)	(2)	(3)
$\log(diversification_{ot})$	0.0024*	0.0033**	0.0033**
	(0.0014)	(0.0014)	(0.0014)
$concentration_{iot}$	0.0052	0.0036	0.0036
	(0.0105)	(0.0093)	(0.0093)
$\log(employment_{it})$	0.0645***	0.0400***	0.0398***
	(0.0026)	(0.0022)	(0.0022)
$\log(age_{it})$	0.0094	0.0145***	0.0136***
	(0.0064)	(0.0043)	(0.0043)
$\log(stock_{it})$	-0.0135**	0.0704***	0.0661***
	(0.0069)	(0.0066)	(0.0068)
$\log(past_i)$			0.0425***
			(0.0125)
industry-year FE	Y	Y	Y
listed status	Y	Y	Y
foreign ownership	Y	Y	Y
weights	N	Y	Y
obs.	35,000	35,000	35,000
r-sq	0.1778	0.2576	0.2582

Notes: The dependent variable is a dummy variable equal to one if the firm opened an establishment in a new 3-digit industry in the past three years. The variable of interest is owner diversification. Controls include ownership concentration, firm employment, firm age, number of active industries, average amount of industry expansion in the firm's five years, listed status, foreign ownership dummy, left-censored dummy, and ind-year FE. Standard errors clustered at the 4-digit industry × year level. significance levels reported – [*** (1%), ** (5%), and * (10%)].

1.4.5 Sector-level relationship

Through firm-level regressions, I document a positive relationship between diversification and risky innovation within 4-digit sector-years. In this section, I examine whether the firm-level relationship survives aggregation to the sector level.

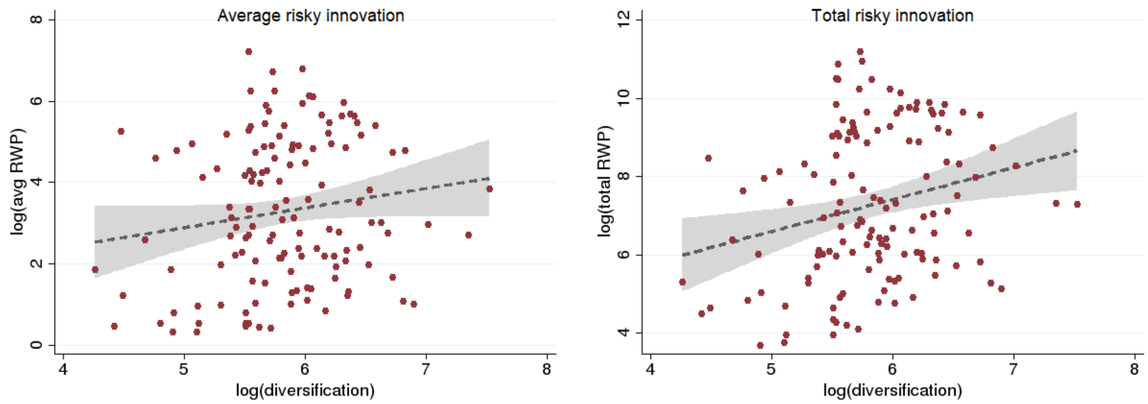
I first plot the simple bivariate relationship between average sector-level diversification and risky innovation, output, and growth; and then estimate the following regression:

$$Y_{st} = \alpha + \lambda log(DIV_{st}) + \nu_s + \nu_t + \varepsilon_{st} \tag{1.7}$$

where Y_{st} is the outcome variable of 2-digit industry s in year t, and includes weighted average risky patenting ($ARWP$), total risky patenting ($TRWP$), total revenue ($Trevenue$), and the revenue growth rate (RG). Both industry (ν_s) and year (ν_t) fixed effects are included to neutralize the effects of industry-specific differences and aggregate conditions.

Figure 1.6 plots the bivariate relationship between weighted average owner diversification at the sector level and weighted average risky innovation (left panel) and total risky innovation (right panel). If diversification is relatively higher in the largest firms, then the relationship between diversification and risky patenting should survive aggregation. Figure 1.6 and the first two columns of table 1.12 confirm the positive relationship. In particular, a 10% increase in diversification is associated with a nearly 5% increase in average risky patenting and 4.4% increase in total risky patenting at the sector level.

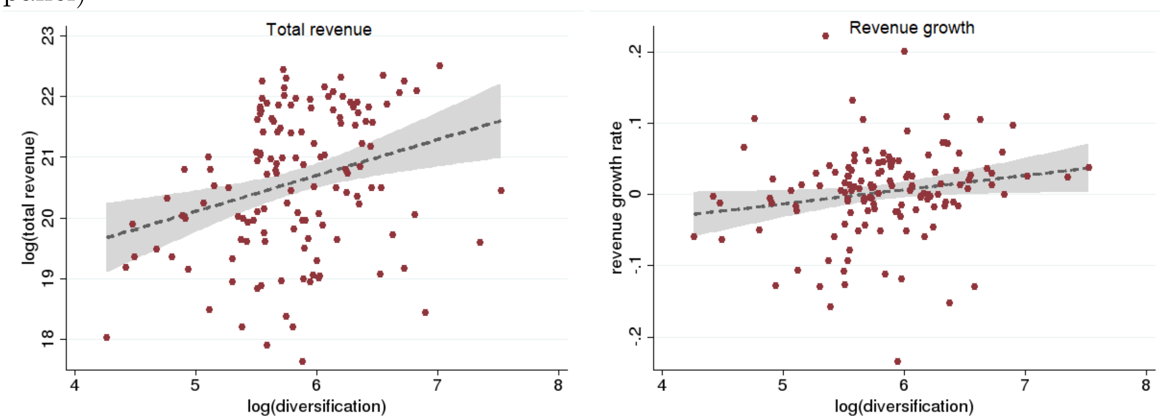
Figure 1.6: Diversification, average RWP (left panel), and total RWP (right panel)



Notes: In both figures, the red dots represent (2-digit NAICS, year) observations. The dotted grey line represents the bivariate linear relationship, and the shaded grey area represents the 95% CI of this relationship. The x-axis in both figures is the log of activity-weighted average diversification. The y-axis in the left panel is log of average activity-weighted risk-weighted patent count ($ARWP$) and the right panel is log of total risk-weighted patent count ($TRWP$).

Figure 1.7 plots the bivariate relationship between weighted average owner diversification at the sector level and total revenue (left panel) and revenue growth rate (right panel). The figure and the last two columns of table 1.12 document a positive correlation between diversification, output, and growth. In particular, a 10% increase in diversification is associated with a 1.2% increase in total revenue and a 0.03 percentage point increase in the revenue growth rate. The positive correlation is suggestive, and can arise from factors outside of risky patenting. The stylized model presented in the next section shows how diversification can generate the patterns observed at the sector level through the risk-sharing channel.

Figure 1.7: Diversification, total revenue (left panel), and revenue growth rate (right panel)



Notes: In both figures, the red dots represent (2-digit NAICS, year) observations. The dotted grey line represents the bivariate linear relationship, and the shaded grey area represents the 95% CI of this relationship. The x-axis in both figures is the log of activity-weighted average diversification. The y-axis in the left panel is log of total revenue ($Trevenue$) and the right panel is revenue growth rate (RG).

Table 1.12: Sector-level: regressions

	$ARWP$	$TRWP$	$Trevenue$	RG
log(diversification$_{st}$)	0.4714**	0.4408***	0.1155*	0.0256**
	(0.1826)	(0.1622)	(0.0660)	(0.0124)
industry FE	Y	Y	Y	Y
year FE	Y	Y	Y	Y
obs.	134	134	134	134
r-sq	0.8751	0.9390	0.9627	0.3208

Notes: The unit of analysis is (2-digit NAICS industry, year). The dependent variables are the log of activity weighted average RWP ($ARWP$) (column 1), log of total risk-weighted patent count ($TRWP$) (column 2), log total revenue ($Trevenue$) (column 3), and revenue growth rate (RG) (column 4). The key control variable is log of activity weighted average owner diversification. Additional controls are industry and year fixed effects. S.E. are robust, and in parentheses [*** (1%), ** (5%), and * (10%)].

1.5 Stylized Model

The empirical analysis establishes that owner diversification facilitates risky innovation. Yet, existing models in the firm dynamics and endogenous growth literatures do not feature the risk-sharing channel that underpins the observed empirical relationship. In this section, I present a static single-agent model of risky productivity-enhancing investment. This stylized model highlights the features needed to activate the risk-sharing channel, and rationalizes the positive relationship between diversification and risky investment documented empirically. I also take a stand on the direction of causality. The model shows that when owners are more diversified, they choose to undertake riskier investments. Through a simple partial equilibrium aggregation exercise, I also show how higher diversification can lead to the higher aggregate output and investment shown empirically.

1.5.1 Setup

There is a single period composed of two sub-periods. Consider an owner who is endowed with n firms. For analytical tractability, it is assumed that the owner has log utility and that all income is consumed without saving.[21] Each firm held by the owner produces via the following production function:

$$y = q^{(1-\alpha)} l^{\alpha} \tag{1.8}$$

[21]The assumption that the number of firms an owner holds is exogenous, and the assumption that all income is consumed without saving is relaxed in the two-period model presented in appendix A.2.

where q is a measure of productivity and l is labor demand, which has a per unit cost of ω. In the second sub-period q is known, l is chosen, and output is produced. Productivity (q) evolves according to the following process:

$$q = \begin{cases} (1+x) & \text{w/ prob. } \lambda \\ (1-x) & \text{w/ prob. } (1-\lambda) \end{cases} \tag{1.9}$$

where x is a choice variable reflecting risky investment and λ is a parameter denoting the probability of success. Investments are chosen in the first sub-period, and are restricted to $x \,\epsilon\, [0, 1]$ to ensure positive output (y). First, the outcome of investment is uncorrelated across firms. Second, consistent with the notion of risky investment, higher investment is associated with higher potential returns, and and a larger gap between productivity in the case of success versus failure. To highlight the role of diversification, it is assumed that there is no additional cost associated with implementing risky investment x. This type of binomial process of risky investment and experimentation is used in the existing literature (Ates and Saffie (2016), Buera and Fattal-Jaef (2016), Choi (2017), Caggese (forthcoming)).

This formulation of risky investment can be thought of as a reduced form representation of firm patenting and/or expansion into new business areas. These activities tend to be associated with uncertain outcomes. R&D efforts may or may not produce new technologies, and patents for these technologies may or may not be filed ahead of competitors researching in similar areas. Successful innovation can increase the efficiency of existing operations and/or create opportunities in new markets. Failures may involve unsuccessful implementation of technologies that are difficult to revert (Caggese (forthcoming)), as well as the kinds of switchover and disruption costs described in Holmes et al. (2012).

Each owner chooses the labor input (l_i) and investment (x_i) in each firm $i \,\epsilon\, [1, n]$ that she owns to maximize his expected utility.

$$\mathbb{E}U = \mathbb{E}\log\Big(\sum_{i=1}^{n}[q_i^{(1-\alpha)}l_i^{\alpha} - \omega l_i]\Big) \tag{1.10}$$

$$\text{s.t.} \quad q_i = \begin{cases}(1+x_i) & \text{w/ prob. } \lambda \\ (1-x_i) & \text{w/ prob. } (1-\lambda)\end{cases} \tag{1.11}$$

Assuming that the period is split into two sub-periods separates the investment and labor decisions. In the second sub-period, q_i is known and the owner chooses l_i to maximize:

$$\max_{\{l_i\}} \quad \ln\Big(\sum_{i=0}^{n}[q_i^{1-\alpha}l_i^{\alpha} - \omega l_i]\Big) \tag{1.12}$$

For each l_i, the solution yields:

$$l_i = \Big(\frac{\alpha}{\omega}\Big)^{\frac{1}{1-\alpha}} q_i \tag{1.13}$$

As a result, when x_i is chosen in the first sub-period, the owner's expected utility is:

$$\mathbb{E}U = \mathbb{E}\log\Big(\sum_{i=1}^{n}\pi q_i\Big) \tag{1.14}$$

where $\pi = (1-\alpha)(\frac{\alpha}{\omega})^{\frac{\alpha}{1-\alpha}}$. Because π is common to all firms, the owner chooses $x_i = x$ for the firms she controls. Using the fact that the probability of success follows a binomial distribution, define $\mathbb{P}(k, n, \lambda)$ as the probability of observing k successes in a binomial process with n trails and success probability λ:

$$\mathbb{P}(k,n,\lambda) = \left(\begin{array}{c} n \\ k \end{array}\right) \lambda^k (1-\lambda)^{n-k} \tag{1.15}$$

In the first sub-period, the owner chooses x to maximize her expected utility:

$$\max_x \sum_{k=0}^{n} \mathbb{P}(k,n,\lambda) \ln(\pi[k(1+x) + (n-k)(1-x)]) \tag{1.16}$$

1.5.2 Solution

A closed form solution for x is available when $n \,\epsilon\, \{1,2\}$. Consider first an owner that holds only one firm. She chooses x_1 to maximize:

$$\lambda \ln((1+x_1)\pi) + (1-\lambda)\ln((1-x_1)\pi) \tag{1.17}$$

which yield the following solution for x_1:

$$x_1 = 2\lambda - 1 \tag{1.18}$$

Now consider an owner that holds two firms. She chooses x_2 to maximize:

$$(1-\lambda)^2 \ln(2(1-x_2)\pi) + \lambda^2 \ln(2(1+x_2)\pi + 2\lambda(1-\lambda)\ln((1+x_2)\pi + (1-x_2)\pi) \tag{1.19}$$

which yields the following solution for x_2:

$$x^2 = \frac{2\lambda - 1}{2\lambda^2 - 2\lambda + 1} \tag{1.20}$$

The analytical results yield a few intuitive insights. First, risky investment is only positive when the probability of success is sufficiently high. As long as $\lambda \,\epsilon\, (0.5, 1]$, x is positive and expected returns are increasing in x. Second, owners controlling two firms choose higher x than owners controlling one firm. This arises because investment outcomes are uncertain and uncorrelated across firms. As a consequence, there is safety in variety. Third, as the probability of success moves towards one, the difference between x_1 and x_2 declines. When $\lambda = 1$, $x_1 = x_2$. This arises because higher uncertainty (lower λ) is associated with a higher gap between success versus failure, which strengthens the risk-sharing channel.

While an analytical solution is unavailable for $n > 2$, the model can be solved numerically to confirm that the positive relationship between x and n remains. Table 1.13 reports the parameter values used in the numerical exercise. Owners are allowed to control up to 10 firm.[22] Figure 1.8 reports the results. The left panel plots the optimal investment (y-axis) against diversification (x-axis) and the right panel plots the resulting expected value (y-axis) for each level of diversification (x-axis). For all n, optimal risky investment (x) and expected value are increasing in diversification (n). As n rises, owners are better able to pool firm-specific risk across their portfolio and optimally choose to undertake riskier investments. Yet, the marginal benefits of diversification are decreasing and the investment policy becomes flat. Each figure reports investment and expected values for different success probabilities (λ), and shows that both are increasing in the success probability.

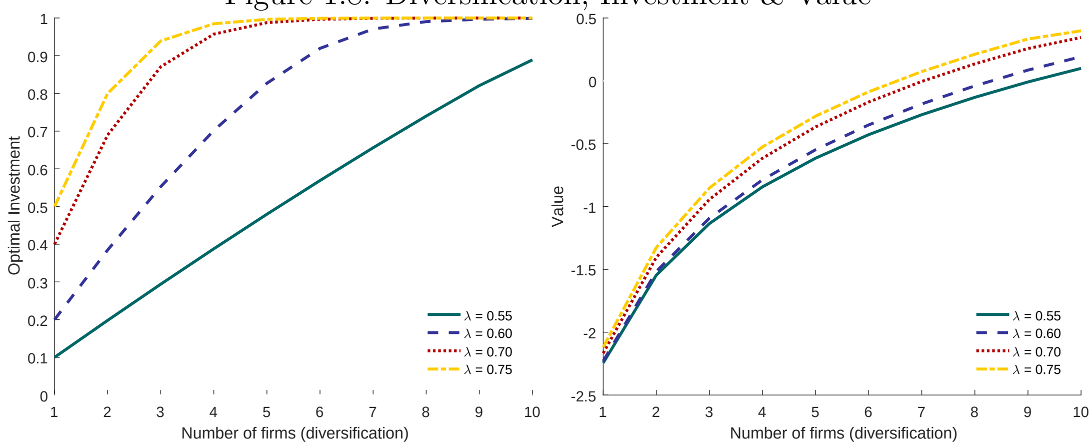
[22]Simulations have been run that allow owners to hold up to 100 firms and the results are qualitatively the same.

Table 1.13: Parameters

Parameter	Value
α	0.75
ω	1.00
λ	$\{0.55, 0.60, 0.70, 0.75\}$

Notes: This table reports the parameter values used in the numerical solution of the model described in section 1.5. α denotes the decreasing returns to scale parameter, ω denotes the per unit cost of labor, and λ denotes the probability that investment will be successful.

Figure 1.8: Diversification, Investment & Value



Notes: The figure in the left panel plots the investment level (x) on the y-axis against the level of diversification (n) on the x-axis. The figure in the right panel plots the expected value on the y-axis against the level of diversification (n) on the x-axis. Each line represents the solution of the model for different values of success probability λ.

1.5.3 Aggregation

I use this stylized model to perform a simple partial equilibrium aggregation exercise to qualitatively show how diversification may generate aggregate outcomes consistent with those observed in the empirical sector-level analysis. This exercise ignores important general equilibrium effects, which would alter the quantitative implications of the exercise, but should not impact the qualitative results. For the exercise, I consider a sector that consists of 100 firms. By doing so, I assume that the law of large numbers does not apply because if it did, idiosyncratic shocks would wash out in aggregate. Recent work by Gabaix (2011), Stella (2015), and Yeh (2017) confirm that firm-level fluctuations do have aggregate implications in the U.S. context. I consider five different scenarios under which the degree of owner diversification is varied, and evaluate the qualitative implications for aggregate investment and output. The owners' problem is described in 1.5.1, and their optimal investment decisions are those reported in section 1.5.2 for the case where $\lambda = 0.55$.

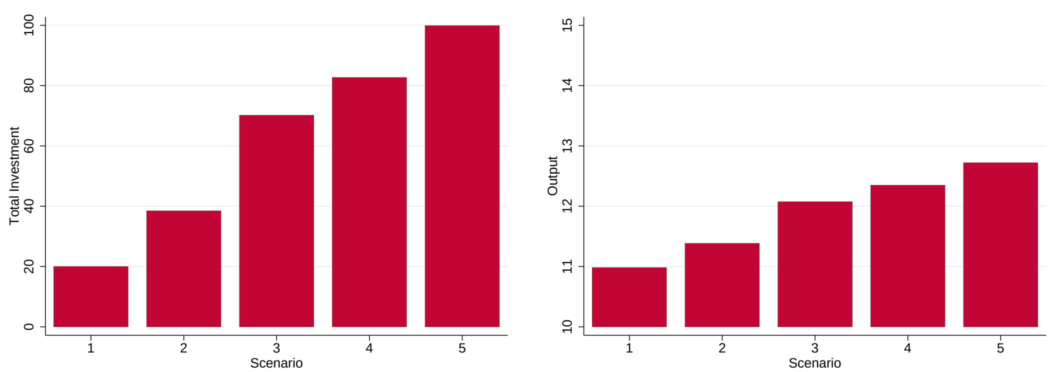
In each scenario, the 100 firms are subject to a series of idiosyncratic shocks (realizations of λ) over a number of periods.[23]. For each firm, the series of idiosyncratic shocks is the same across the scenarios. The only thing that varies across scenarios is the degree of owner diversification. In the first (1) scenario, there are 100 owners, each controlling only one firm. This is the scenario with the lowest degree of owner diversification. In the second (2) scenario, there are 50 owners, each controlling two firms. In the third (3) scenario, there are 25 owners, each controlling four firms. In the fourth (4) scenario, there are 20 owners, each controlling five firms. And in the fifth (5) scenario there are 10 owners, each controlling 10 firms. This last scenario represents the highest degree of owner diversification.

Figure 1.9 shows that investment and output is increasing in the degree of owner diversification. Investment and output are lowest in the scenario in which firms are controlled by owners holding only one firm and highest in the scenario

[23]The model is simulated for 5,000 periods. The figures report the average value of sectoral output and investment for the last 200 period

in which firms are controlled by owners holding 10 firms. Under scenario 1, the investment in each of the 100 firms is $x = 0.20$, which reflects the optimal investment of the 100 investors that hold one firm each. Under scenario 5, the investment in each of the 100 firms is $x = 0.99$, which reflects the optimal investment of the 10 investors that hold 10 firms each. As a consequence, aggregate investment is 20 in scenario 1 and 99 in scenario 5. Investment is successful in approximately 60% of firms in each case. As a consequence, output is approximately 11 under scenario 1 and 13 under scenario 5. Because the model is stylized, and the aggregation exercise ignores general equilibrium effects, the takeaway is qualitative. Sectors characterized by higher average diversification are associated with higher risky investment and output, which is qualitatively consistent with the sector-level findings documented empirically.

Figure 1.9: Investment (left panel) and Output (right panel)



Notes: The figure in the left panel plots total investment on the y-axis for five different scenarios. The figure in the right panel plots the total output on the y-axis for five different scenarios. In scenario 1 there are 100 owners each holding one firm; in scenario 2 there are 50 owners each holding two firms; in scenario 3 there are 25 owners each holding four firms; in scenario 4 there are 20 owners each holding five firms; and in scenario 5 there are 10 owners each holding ten firms.

1.6 Conclusion

Recent work establishes that risky innovation contributes disproportionately to aggregate growth (Akcigit and Kerr (2018)). The factors that incentivize firms to engage in this type of innovation are not yet fully understood. In this paper, I study owner diversification, which prior literature emphasizes as an important determinant of firm decisions-making. In particular, I examine whether firms held by owners with more diversified business interests engage in riskier innovation, whether the relationship arises through risk-sharing channel, and whether the firm-level relationship has implications for sector-level outcomes.

I first tackle the question empirically. To do so, I construct a novel dataset that combines ownership information from Moody's Bureau van Dijk database for a a sample of privately-held and publicly-listed U.S. firms, with patenting data from the USPTO and other firm-level data from the Census Bureau. The data provide a rich set of time varying firm-level and owner-level controls. The panel nature of the data also allow me to exploit variation in risky patenting within firms and variation in diversification within owners over time. In a first-difference specification that accounts for both time-varying and time-invariant firm and owner characteristics, I show that higher owner diversification incentivizes more risky innovation. The results can be interpreted as causal as long as owner diversification and remaining unobserved firm and owner characteristics are orthogonal. To address an alternative story that posits the positive relationship arises solely from riskier innovation incentivizing higher owner diversification, I show that changes in risky innovation are higher among firms held by initially more diversified owners. The rich set of controls and the empirical approaches employed in this paper lend credence to a causal interpretation of the empirical findings. The results provide new evidence on the importance of owner diversification in incentivizing risky innovation and pave the way for studying the relevance of the risk-sharing channel and aggregate implications of owner diversification.

To test whether the positive relationship between owner diversification and risky innovation arises due to risk-sharing, I classify owners as individuals, corporations, and institutional owners. Individual owners are most exposed to firm-level risk, followed by corporations and institutional owners. Consistent with the risk-sharing mechanism, I document that the positive relationship between risky innovation and owner diversification is strongest among firms held by individual owners. To examine the sector-level implications of owner diversification, I exploit cross-sector variation and document a positive relationship between sector-level diversification and risky innovation, revenue, and revenue growth, after accounting fixed effects that account for industry-specific and aggregate conditions.

The empirical results suggest that the risk-sharing channel plays a role in firms' risky innovation decisions. I develop a stylized model in which I take a stand on the direction of causality and show how higher owner diversification leads to riskier investment. The model features risk-averse owners, multi-firm ownership, and risky productivity-enhancing investment. Because investment outcomes are uncertain and uncorrelated across firms, owners face idiosyncratic risk from the firms in their portfolio. Through the lens of this simple model, I show that consistent with the firm-level empirical findings, more diversified owners find safety in variety and choose riskier investment because they are better able to share idiosyncratic risk across the firms they hold. Moreover, through a simple partial equilibrium aggregation exercise, I show that consistent with my sector-level empirical findings, higher sector level diversification endogenously gives rise to higher investment and output.

In this paper, I establish owner diversification as an important factor in facilitating risky innovation. My findings suggest promising areas for future research. The stylized model introduced in this paper can be embedded into a standard firm dynamics model in order to study the quantitative implications of owner diversification for aggregate innovation and growth. Empirically, the newly constructed data can be used to study whether owner diversification matters for other risky investment strategies, such as expansion into new domestic and foreign markets. It can also illuminate whether owners' internal networks facilitate firm-level investment and innovation through technology spillovers and vertical integration. This paper and complementary lines of research provide important and interesting new insights into how ownership structure affects firms' willingness and ability to undertake growth-enhancing investments.

Chapter 2: Leverage over the Life Cycle & Implications for Firm Growth & Shock Responsiveness[1]

2.1 Introduction

There is an extensive literature studying the growth and employment dynamics of the U.S. firms over their life-cycle. Far less is known about how these firms finance their growth. Much of what is known about firms' financing behavior derives from publicly-listed, relatively large and old firms in Compustat. Yet, the behavior of private firms, which are much younger and smaller on average, has important macroeconomic implications since these firms account over 70 percent of aggregate US employment and over 55 percent of aggregate US gross output, and they are the ones that are most susceptible to the effects of financial shocks that impede lending and borrowing.[2]

Our aim in this paper is to better understand how firms at different points in their life-cycle choose to (or are able to) finance their operations and the implications

[1]This chapter is coauthored with Emin Dinlersoz, Sebnem Kalemli-Ozcan and Henry Hyatt.

[2]As we show in detail in our data section below, between 2005 and 2012, listed, non-financial firms accounted for around 25 percent of domestic employment and 46 percent of domestic gross output in the U.S. Using financial data for private non-financial firms in the United Kingdom, Zeltin-Jones and Shourideh (2016) documents that private firms finance nearly 80 percent of their investment using financial markets compared to only 20 percent among listed firms, and private firms disproportionately account for the transmission of financial shocks to the economy.

of this life-cycle financing on firm growth and responsiveness to aggregate shocks. We construct a new data set on firm financing over the life-cycle using balance sheets of both publicly-traded and privately-held firms matched to the U.S. Census Bureau's Longitudinal Business Database (LBD). We refer to our new data set as LOCUS, that combines LBD, "L", with balance sheet data of privately-held firms from Bureau van Dijk's Orbis, "O", and publicly-listed firms from Standard & Poor's Compustat, "C", for the United States, "US". Our new data set, LOCUS, allows us to compare the relatively understudied behavior of leverage for private firms with that of the large listed firms, which has been the main focus of the existing literature. We explore leverage both in cross-section and over time, as a function of the life-cycle dynamics of firms – proxied by their age and size. Once we establish these patterns, we focus on the implications of firms' financing on their growth and their response to shocks, particularly to the financial crisis of 2007–2008.

The firm dynamics literature has established that, conditional on age, firm growth is negatively related to the size of the firm. It is also the case that conditional on size, firm growth is negatively related to the age of the firm (e.g. Davis et al. (1996)). Benchmark models of firm growth, such as Jovanovic (1982) and Hopenhayn (1982), cannot account for these *conditional* dependencies. In such models, firms of the same age experience the same growth rate independently of their size. Cooley and Quadrini (2001) show that adding financial frictions to these models in the form of costly default and equity issuance can account for these life-cycle dynamics, since financial frictions cause firm size to depend not only on firm's productivity but also on equity. Albuquerque and Hopenhayn (2004) can also account for the firm dynamics observed in the data, though in their model financial frictions arise due to imperfect enforceability.

We can test main predictions of these firm dynamics models with financial frictions using our new U.S. firm-level data, LOCUS. This exercise will lead to two main contributions that are relevant for the literatures both on firm dynamics and financial frictions. First, despite having plausible theoretical mechanisms for generating realistic firm dynamics, there is very little evidence on the role of financial frictions in these dynamics. Second, models of financial frictions have very different predictions on how firms of different ages and sizes will borrow, and why. For example, the models of Cooley and Quadrini (2001) and Albuquerque and Hopenhayn (2004) predict different relationships between firm size and leverage. The former model implies that smaller, younger and more productive firms have higher leverage, and leverage declines over time as firms increase their equity. Hence, size and leverage are negatively associated conditional on age and productivity. In contrast, Albuquerque and Hopenhayn (2004) implies that larger and more productive firms have larger projects financed with long-term debt. Over time as firms' equity grow, firms pay down their long-term debt, which relaxes the borrowing constraint on the short-term debt. Therefore, as firms grow, they incur more short-term debt, leading to a positive relation between firm size and leverage based on short term debt. Total leverage (sum of short-term and long-term debt) and size might still be negatively related. Both of these models also predict a negative relation between age and leverage since young firms borrow more. There are other models of financial frictions such as Buera and Moll (2015) that assume that firms operate a constant returns technology and hence all firms have the same borrowing limit, and there is no heterogeneity in firm leverage by firm age and size.

Our results show extensive heterogeneity in leverage by firm age and size among private firms.[3] In the cross section of private firms, larger firms are more leveraged regardless of the maturity of the debt and they have less equity as a fraction of their assets. Over time, as private firms get older, their leverage decreases, both in terms of short-term and long-term debt, and their equity increases as a fraction of assets. Small private firms are the least leveraged, but young private firms are the most leveraged, indicating that size and age have different relationships with leverage for private firms. The negative relationship between age and leverage is most likely driven by firms starting out at a size that is below their efficient scale, and so new firms choose to borrow more than older firms.

For public firms, the relationship between short-term leverage and size is weak and slightly negative. In contrast, very large public firms have high leverage in terms of long-term debt. This compositional effect results in no robust relation between total leverage and size for public firms. At the same time, equity-size relationship has an inverted U-shape for public firms. Since these firms have access to external equity via stock issuances, they issue less external equity and turn toward long-term debt borrowing as they become larger. Compared to private firms, the relationship between age and leverage is far weaker among public firms for all measures of leverage. Public firms appear to slightly reduce their equity as they age, which

[3] The relationships between leverage and size (or age) are conditional on all other firm-level observables that can influence leverage, which we control for in our analysis.

is consistent with them being leveraged in long term debt as they grow older and become larger.

What do these result imply for firm growth and response to aggregate shocks? Borrowing constraints of firms play a critical role in macroeconomic analyses when there are financial frictions. In the models such as Holmstrom and Tirole (1997), cash flows determine the constraint, whereas the liquidation value of physical assets that firms can pledge as collateral is important in models such as Hart and Moore (1994); Schliefer and Vishny (1992); Bernanke and Gilchrist (1999), Kiyotaki and Moore (1997), Mendoza (2010), Jermann and Quadrini (2012), Moll (2014), Buera and Moll (2015), Evans and Jovanovic (1989), Brunnermeier and Sannikov (2014).[4] No matter how the borrowing constraint is determined, this literature typically abstracts from firm heterogeneity and firm dynamics to mainly focus on short-term borrowing behavior represented by a one-period borrowing constraint that limits the amount a representative firm can borrow to some linear function of its assets. The constraint can also include the aggregate price of capital as in Bernanke and Gertler (1989), Virgiliu and Xu (2014).

At the same time, a large body of work in macro and corporate finance literatures seeks to understand the effect of firm heterogeneity on sales, investment, and employment responses of firms to aggregate shocks, where these shocks lead to tightening of credit such as financial crises or contractionary monetary policy. Models such as Cooley et al. (2004), Khan and Thomas (2013), Gopinath et al.

[4] Lian and Ma (2015) show that, in a sample of listed firms, large firms' constraints are determined by cash flows, whereas small firms are more dependent on asset values.

(2017), Quadrini (2000), Cagetti and De Nardi (2006), Dinlersoz et al. (2017) put firm heterogeneity at the heart of financial constraints. These constraints play an important role in the propagation of aggregate shocks. The seminal work by Gertler and Gilchrist (1994), shows that adverse shocks are propagated via small firms' constraints in access to capital markets; that is, the financial accelerator mechanism works via credit constraints for small firms.

The empirical literature is divided on the role of heterogeneity in the transmission of monetary policy. While there are many empirical papers using data on listed firms from Compustat that show a higher sensitivity of small firms to credit tightening measured as recessions or monetary policy tightening (e.g. Farre-Mensa and Ljungqvist (2016), Rajan and Zingales (1995), Whited and Wu (2006)), there are others that use confidential data on select private firms from QFR database of Census Bureau and show that large firms respond more in terms of sales, inventories, short-term debt and employment (e.g. Kudlyak and Sanchez (2017), Chari et al. (2013)).[5] Even if small firms are more sensitive to shocks, the difference is not meaningful economically and also cannot be explained by financial frictions as shown by Crouzet and Mehrotra (2017). Using aggregate public data from the U.S. Census Bureau's Business Dynamics Statistics (BDS), Moscarini and Postel-Vinay (2012) also find that in the previous recessions, large firms suffered more than small firms in terms of employment; a finding confirmed by Kudlyak and Sanchez (2017) for the Great Recession. Fort et al. (2013) argue that this literature fails to separate

[5]The latter paper shows that greater sensitivity of small firms is not robust to all time periods and in most recessions since 1950s the response of small and large firms were similar.

the role of age and size.[6] In particular, QFR does not contain measures of firms' age, whereas Compustat does not include age and it measures employment using a firm's global operations, not just the U.S. domestic employment. LBD and BDS databases of the Census Bureau, instead, provide both domestic employment and age measures for all private and public firms in the U.S. This coverage is key since different shocks (financial versus demand) and different cyclical episodes (monetary policy changes versus unemployment spells) might affect the response of small and large firms differentially conditional on their age. Using BDS and focusing on a longer time span, Fort et al. (2013) find that young/small business are more sensitive to businesses cycle shocks.

It has also proven difficult to map firm size to financial constraints via variables on actual borrowing such as leverage, short-term debt and liquid assets. Crouzet and Mehrotra (2017) shows that there is no difference by firm size in the behavior of short-term debt and bank debt as a response to business cycles. On the other hand, matching listed firms from Compustat to their establishments in LBD data, Giroud and Mueller (2017) show that firm leverage is important in propagation and when house prices dropped employment fell significantly more in establishments belonging to more leveraged listed firms. Jeenas (2018), using listed firms from Compustat, shows that highly leveraged firms are *more* responsive to monetary policy shocks in terms of investment, since they decrease investment more after a monetary policy contraction. Using Compustat data and similar high frequency identification of monetary policy shocks, Ottonello and Winberry (2018) find exact opposite result

[6]For instance, Moscarini and Postel-Vinay (2012) does not condition on age.

that highly leveraged firms are *less* responsive to monetary policy shocks, that is, after a monetary policy contraction, these firms invest more. Papers that identify credit supply shocks directly show that small and young firms are affected more by such shocks (e.g. Chodorow-Reich (2014), Chodorow-Reich and Falato (2017), Gilchrist et al. (2018).)

We argue that in order to identify the link between firm size, leverage and financial constraints, three ingredients are key: First, one has to condition on age. Second, the dataset has to encompass full size distribution covering the range of small firms, and third, size should be measured with employment. We believe, most of the previous findings in the literature reflect differences in the growth and financing policies of firms at different stages of firms' lifecycles. Firms' need for internal versus external finance will vary with their lifecycle and firms which use external finance will be more susceptible to credit shocks. In that sense, large firms, by having a greater access to credit, might be more negatively impacted during periods of credit crunch. On the other hand, very large firms can also substitute between bank and market debt. Similarly, very small firms might have limited access to credit during both normal times and crisis times and hence hard to identify the effect of shocks on such firms. As a result, higher leverage in terms of short-term debt may not be mapped directly to being financially constrained and thus coverage of both small and large firms is essential.[7] Our finding that short-term leverage ratios

[7] Kalemli-Ozcan et al. (2018), using ORBIS data for private firms for several European countries, show that firms who entered the crisis with higher leverage in 2009, decreased their investment more in the aftermath of the crisis. They also show that larger firms, who invest less during normal times, invested more during the crisis time. This result supports the conjecture that highly leveraged firms become financially constrained during the crisis when the credit conditions tighten. Not all *large firms* are highly leveraged and this allows to identify different roles for leverage and

are higher in larger "private" firms but lower in larger "public firms" supports this line of argument. And finally, employment is a better measure of size than assets. Most papers measure size with assets and typical small firm measure of 25th-30th percentile in sales or assets will correspond to firms with assets less than 1 billion, which is not small. In addition depending on whether assets are measured at book value or at market value, a size measure based on assets will fluctuate more (or less) than a size measure based on employment even though the firm is actually not growing or shrinking.

In models of financial frictions, firms sometimes do not borrow because they operate at an efficient scale, and sometimes because they are unable to access credit. Our finding that leverage ratios are higher in larger firms may be driven by larger firms having better and larger projects to finance, and therefore demand more credit, or lenders may be more willing to lend to larger firms and hence small firms are credit constrained. We argue that size being an important correlate of leverage for private firms is at least in part driven by credit constraints that differentially affect small firms. To test this implication, we use the "Great Recession" as a shock to financial conditions, which can make financial frictions matter more for already constrained firms and also for firms who become constrained when credit conditions tighten. In fact, this is exactly what we find. For private firms, it is not only that small firms have even lower leverage, but also larger private firms are affected from the crisis and decrease their borrowing relative to their assets. Short-term leverage is more

size in determining investment, where both large and low leveraged firms invest more when credit frictions tighten.

strongly associated with size in the pre-crisis period than during the crisis period, i.e. the size differential contracts during the crisis. This finding is similar to the papers that find that larger firms respond more to the episodes of credit tightening. Our results suggest that some firms might be credit constrained both in normal and crisis times (small private firms) and some firms might become more constrained during the crisis times (large private firms) and some firms are never appear to be constrained (large public firms).[8]

Our results condition on standard determinants of leverage such as collateral/tangibility and sector-year fixed effects and firm-level profitability in order to account for sector and firm level demand shocks, which allow us to interpret the variations in actual amount of borrowing stemming mostly from variations in the maximum amount firms can borrow (financial constraints), where this amount changes across firms of different sizes and ages. In other words, our underlying assumption is that, conditional on observables that can affect demand for borrowing, for a given firm size (or age) level there are enough financially constrained firms that the average leverage of firms reflects the underlying borrowing constraint for that level. We also condition on labor productivity as an additional proxy for growth potential and underlying productivity of firms. The estimates on firms' productivity further supports our access to finance/financial frictions interpretation, since more productive firms, conditional on age and size, have higher short-term leverage as predicted, but only if these firms are private firms. There is no relation between

[8] Using financial data from the universe of firms in Canada, Huynh et al. (2018) obtain results that are similar to our results from the U.S. They find that private firms have more leverage than public firms, driven by the fact that private firms rely more on short-term debt compared to public firms.

productivity and short-term leverage for public firms. Productive public firms have higher leverage based on long-term debt, whereas the relationship between productivity and long-term leverage is insignificant for private firms. These results suggest that smaller private firms have more difficulty accessing long-term financing, even if they are productive. The firm fixed effect panel specification that uses "within" variation show the robust relationship between firm size and short-term leverage, further supporting our interpretation. This result is noteworthy since in general the literature using listed firms find very persistent patterns in leverage, where firm fixed effects specifications lead to insignificant connection between leverage and its determinants, collateral, profitability and size (e.g. Lemmon et al. (2008).)

Our results in terms of firm growth are as follows. We show that leverage and firm growth are strongly positively correlated for private firms in the cross section both during normal times and during the crisis. In the firm fixed effect panel specifications, this positive result weakens during the crisis, which suggests that financial constraints might become more binding for a larger set of private firms during the crisis. If these firms finance their growth with leverage during normal times and cannot borrow as much during crisis times, then the relation between growth and leverage should become weaker, when we identify this relation from within firm variation. By contrast, public firms' growth is negatively related to their short-term leverage in normal times and this relation is not affected by the crisis. This result is consistent with public firms not being financially constrained, but rather slow-growing large public firms being leveraged. In addition, size has no differential affect on firm growth during crisis only when we control for short-term leverage, which suggest that size is a good predictor of financial constraints that is captured by short-term leverage.

We proceed as follows. Section 2.2 reviews the literature. Section 2.3 describes the data and presents detailed statistics on the share of aggregate US economic activity accounted by listed firms. Section 2.4 describes the empirical methodology and results. Section 2.5 concludes.

2.2 Literature

In this section, we provide a brief survey of the literatures that our paper relates to. We start with the literature on firm borrowing and financial constraints and its implications on how firm age and firm size may be related to both the borrowing behavior and the financial constraints firms face.

A large number of studies have proposed models in which agents borrow in order to finance projects. Contributions such as Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) introduce financial frictions into standard macroeconomic models and demonstrate that financial frictions have substantial ability to amplify business cycle fluctuations.[9] In most models, the borrowing constraint takes the generic form

$$b_t \leq \theta k_t \tag{2.1}$$

where t denotes time, b_t is debt, k_t is capital (or assets) and θ is a constant

[9] Kiyotaki and Moore (1997) propose an extension of their representative agent framework in which only some firms have investment opportunities in any given period while those firms without investment opportunities will pay down their debts. This extension of their model therefore might predict a positive relationship between borrowing and size.

that limits debt to a fraction of assets. Capital can be a function of aggregate prices (e.g. $k_t(P_t)$), in order to generate the financial accelerator mechanism via valuation of assets. Another version of this constraint may include interest rate, R_t. In that case the constraint can be written as

$$R_t b_t \leq \theta k_t \tag{2.2}$$

Most of these models abstract from entry, firm growth and exit, and make no predictions about the relationship between borrowing and firm age. Other contributions in the macro literature, such as Mendoza (2010) and Jermann and Quadrini (2012), employ representative agent models and do not make cross-sectional predictions about the relationship between size and borrowing behavior. In such models, the borrowing constraint binds, $b_t = \theta k_t$. Clearly, this class of models will imply constant leverage in the cross-section of firms. Given the firm-level heterogeneity in the data, we explore a model in which there is such heterogeneity.

There is a set of models that introduce heterogeneity in productivity among firms. This heterogeneity leads to a firm size distribution. However, when firms operate constant returns to scale technologies, firms borrow as much as they can up to a borrowing constraint. This is the case in models such as Moll (2014) and Buera and Moll (2015), where firms always borrow as much as they can, implying that the ratio of borrowing to total assets, and hence leverage, does not vary among active firms, and the leverage is the same for firms of different sizes. Hence, it is not possible to obtain predictions about differences in cross-sectional financial frictions relating to firm size and firm leverage.

Richer predictions on how borrowing behavior may be related to firm size and firm age come from the smaller set of studies in which firms operate decreasing returns to scale technologies. For instance, Cooley and Quadrini (2001), Khan and Thomas (2013), and Crouzet and Mehrotra (2017) introduce financial frictions into models of industry dynamics. A decreasing returns to scale technology is also a common modeling choice in the entrepreneurship and occupational choice literature as in Cagetti and De Nardi (2006), Buera and Shin (2013), Bassetto et al. (2015), and Dinlersoz et al. (2017).[10] In most of these models, the borrowing constraint a firm faces is specified again as a short term (one-period) constraint, where borrowing is limited to some multiple of the entrepreneur's current capital or assets. The multiple can be a constant (e.g. Evans and Jovanovic (1989), Quadrini (2000), Cagetti and De Nardi (2006)), as in the above equations, or a more general function of the firm's productivity or capital stock (e.g. Virgiliu and Xu (2014), Khan and Thomas (2013)).[11]

These models generally imply that entrepreneurs with more productive (larger) projects take out larger loans than those with less productive (smaller) ones, and with predictions about borrowing behavior by firms as they age and grow.[12] Decreas-

[10]While some models assume all firms employ a decreasing returns to scale technology, models such as Cagetti and De Nardi (2006), Bassetto et al. (2015), and Dinlersoz et al. (2017) distinguish between an entrepreneurial sector in which firms are operated by households using a decreasing returns to scale technology, and a corporate sector which is characterized by a constant returns to scale technology. In these models, financial constraints apply only to the entrepreneurial sector.

[11]In Gopinath et al. (2017), although firms operate under CRS, the limit on borrowing is a convex function of firm's capital, implying that the constraint on borrowing relaxes as a firm grows, but at a decreasing rate. This models also implies larger firms are more leveraged.

[12]In some of these models, there is an important distinction between the predictions on firm size unconditionally, and conditional on age. Because all firms start out small, the set of large firms contains many that have paid off their debts. Hence, borrowing declines in firm size in Figure 3 of Cooley and Quadrini (2001) (page 1296). But conditional on age, firms that borrow more are those that experience better productivity shocks.

ing returns to scale implies that firms have an optimal size, and as firms approach this size, the incentive to borrow and the amount borrowed as a fraction of firm's assets naturally lessens. A natural prediction of these models is that firm leverage should be decreasing in age.[13]

Models in which entrepreneurs operate such decreasing returns to scale technologies make more ambiguous predictions about how borrowing will vary by firm size, which also vary with specific modeling choices. In most such models, businesses with better ideas will want to borrow more than those with worse ideas. In most cases, this leads to larger businesses having more leverage, at least very soon after entry. Indeed, Hurst and Lusardi (2004) argue that the vast majority of entrepreneurs do not require a large loan to operate their businesses at an efficient scale and so are not credit constrained. Cagetti and De Nardi (2006) reconcile this finding with this class of models via a calibration in which only the largest businesses are affected by credit constraints because most business owners provide all needed finance. The longer term differential depends on the speed of debt repayment. However, this size-leverage depends on the way that financial frictions are modeled. In Cooley and Quadrini (2001) financial frictions are modeled via default risk that is priced with an interest rate differential rather than a borrowing limit. Financial intermediaries share the costs of default, which in turn induces smaller, riskier businesses of any age to borrow more. However, when financial intermediaries choose the size of loans (i.e., have a borrowing limit that is endogenously determined) as

[13] A similar approach is taken by Clementi and Hopenhayn (2006). In their framework like many others with a concave production technology, firms start with a large initial investment pay down their debts over time. However, heterogeneity among firms is beyond the scope of their study and so does not offer predictions of borrowing where size is conditional on age.

in Albuquerque and Hopenhayn (2004), more productive businesses may be allowed a higher leverage ratio than smaller ones since they are further away from the exit threshold.

A smaller number of studies on financial frictions endogeneize borrowing and distinguish between short term and long term debt, including Diamond (1991), Albuquerque and Hopenhayn (2004), and Alfaro et al. (2016). The model in Albuquerque and Hopenhayn (2004) features firm dynamics that is driven by a sequence of revenue shocks over time, which generates predictions regarding borrowing behavior and constraints by firm size and age over the life-cycle of firms. A firm needs to raise an initial amount of capital to start operation, and may also need to borrow in subsequent periods to finance production. Rather than being exogenously given, borrowing constraints naturally arise due to the limited enforcement of contract between the firm and the lender, and the resulting incentives – the lender does not necessarily provide all the startup capital to the firm in order to prevent the entrepreneur from running away with some of that capital. Importantly, the model distinguishes between short term and long term debt, which are both endogenously determined and related to each other. As a firm grows, it builds equity, and gradually pays down its debt. The higher a firm's long term debt, the less capital it is able to borrow for current production, resulting in a negative relationship between long term and short term debt. Firms therefore aim to pay their long term debt as quickly as possible to render short term borrowing constraint non-binding.

The Albuquerque and Hopenhayn (2004) model has several predictions on the firm life-cycle dynamics of debt.[14] Firms with prospects of better revenue (productivity) shocks and growth opportunities are associated with more debt initially, exhibit lower failure rates, pay off their long-term debt faster, and eliminate their short-term borrowing constraint quicker. At any point in time, larger firms have more leverage and long-term debt, conditional on the revenue shock. As the equity of an entrepreneur grows, debt maturity also changes: short-term debt increases relative to the long-term debt. In general, short term borrowing constraints relax as a firm grows, and firms can eventually become non-dependent on external financing as they continue to pay off long term debt and the accumulated equity becomes sufficient to finance the firm. Therefore, conditional on the size of the firm, older firms have lower debt.

Most models in this literature impose a short-term borrowing constraint represented by a one-period limit on how much a firm can borrow to finance production. The predictions from models that feature firms with a constant returns to scale technology and a borrowing limit that is independent of firm size are rather stark and suggest that firm borrowing behavior should be independent of firm size.

Our paper is also related to a large literature that tries to understand the determinants of listed firms' balance sheet structure and its effects on investment and hiring decisions. The seminal work of Rajan and Zingales (1995), using data

[14]Here, we note the model's general predictions. Albuquerque and Hopenhayn (2004) also specify a special case in which lenders coordinate on both the availability of credit as well as the borrowing limit, in which case overall debt can be written as a sequence of short-term contracts, and the model exhibits dynamics of total debt in which the borrowing constraint can be characterized by Equation 2.1, where θ is a function of prior borrowing, and the firm's productivity draw. But in their more general case, a firm's level of long-term debt is given by an incentive compatible sequence of repayments that solve a recursively defined default problem, and only short-term debt is characterized as in Equation 2.1.

on non-financial publicly listed firms in G-7 countries in late 1980s, document that size, profitability, and collateral are the most important determinants of leverage of firms. More recently, Custodio et al. (2012) document a rising reliance on short-term debt among U.S. listed firms, particularly driven by small firms who face higher information asymmetry and choose to issue more public equity. Ajello (2016) finds that between 1989 and 2008, thirty-five percent of U.S. listed firms' investment is funded using financial markets. Similar to Ajello (2016), Covas and Den Haan (2012) show listed firms finance investment with both debt and equity, and that both forms of financing are more pro-cyclical for smaller listed firms. Begenau and Salomao (2015) find that while large firms are able to substitute between debt and equity over the business cycle, small firms' debt and equity are both procyclical.

2.3 Data

We argue that a new database is needed that covers the financial accounts of private firms since listed firms in the U.S., account a small of portion of the economic activity. Between 2000 and 2013, around 6,600 firms were actively publicly traded annually, which accounts for a mere 0.13 percent of all firms in the economy.[15] Less clear is the fraction of employment and revenue that these firms account for. This

[15]The 6,600 figure is arrived at by beginning with Compustat and 1) keeping one observation per (gvkey, year) pair; 2) keeping (gvkey, year) pairs with a positive security price in the indicated year or in the years that bracket the indicated year, as in Davis et al. (2006); 3) dropping financial instruments (ETFs, ADRs, etc), which involves dropping observations with missing NAICS codes and those with NAICS equal to 525; 4) dropping non-U.S. firms, which involves dropping observations with simultaneously missing EIN and state information or those with simultaneously missing EIN and a non-U.S. address; and 5) dropping firms in public administration (NAICS code 92). The 0.13 percent figure is arrived at by dividing 6,600 by 5,020,309, which is the average number of firms in the U.S. economy between 2000 and 2013 derived from the Census Bureau's Business Dynamic Statistics data.

section attempts to shed light on this topic by relying primarily on publicly-available data.

Total U.S. employment is obtained from the Census Bureau's Business Dynamic Statistics (BDS). The BDS is derived from the LBD and covers 98 percent of private employment. Data are available annually and can be broken down by firm size, age, location, and sector. This section uses the economy wide and sector tables. The total employment reported in the economy wide table is used to calculate the contribution of listed firms to total U.S. employment. The sector table includes 9 broad sectors – agriculture, forestry, and fishing (AGR); mining (MIN); construction (CON); manufacturing (MAN); transportation, communication and public utilities (TCU); wholesale trade (WHO); retail trade (RET); finance, insurance, and real estate (FIRE); and services (SRV). This table is used to calculate the contribution of non-FIRE listed firms to total non-FIRE U.S. employment by taking the total employment reported in the economy-wide table and subtracting from it employment in FIRE reported in the sector table. The second statistic is reported because this paper focuses on the non-financial sector.[16]

Total U.S. gross output is obtained from the Bureau of Economic Analysis' Industry Economic Accounts. Gross output measures sales, including those to both final users and other industries and is measured in current prices.[17] Total gross

[16]This paper excludes only the finance and insurance sectors (NAICS code 52). The BDS groups finance and insurance (NAICS 52) with real estate, rental and leasing (NAICS 53). As a result, when calculating the contribution listed firms to employment and revenue in non-financial sectors, this section excludes FIRE (NAICS codes 52 and 53) from data informing both the numerator (Compustat) and denominator (BDS and BEA).

[17]Given the BEA definition of gross output, this measure corresponds to the revenue variable observed in Compustat. While the BEA provides data on gross output, other sources such as the BLS do not include this variable.

output by private industries is used in calculating the contribution of listed firms to total U.S. gross output. Total gross output by private industries net of the finance, insurance, real estate, rental and leasing sectors (FIRE) is used in calculate the contribution of non-FIRE listed firms to total non-FIRE U.S. gross output.

Calculating the contribution of listed firms to U.S. employment and gross output is not straightforward for two reasons. First, not all firms in Compustat are actively traded. Following Davis et al. (2006), this paper defines active listed firms as those with a positive security price in a particular year or in the years that bracket that year. Second, and more importantly, as noted in Davis et al. (2006), while the LBD measures the total number of employees that are subject to U.S. payroll taxes and total domestic revenue, Compustat measures the total number of employees and revenue of domestic and foreign subsidiaries. These differences in the concepts give rise to discrepancies between the LBD and Compustat reported employment and revenue. Similar to Davis et al. (2006), this paper compares the LBD and Compustat employment and revenue of matched firms. Between 2007 and 2013, LBD employment is only 75 percent of Compustat employment and LBD revenue is only 79 percent of Compustat revenue. It is therefore important to adjust the employment and revenue reported in Compustat when calculating the contribution of listed firms to the U.S. economy because the BDS measures only domestic employment and the BEA measures only domestic gross output.

To highlight the importance of taking into consideration these two factors, this paper reports several alternative measures of listed firms' contribution to the U.S. economy:

1. The first version (labeled "raw" in the figures) sums Compustat reported employment (variable emp) and revenue (variable revt) across all listed firms and divides it by total BDS employment and BEA gross output.[18]

2. The second version (labeled "active" in the figures) sums Compustat reported employment and revenue across all actively traded listed firms and divides it by total BDS employment and BEA gross output.

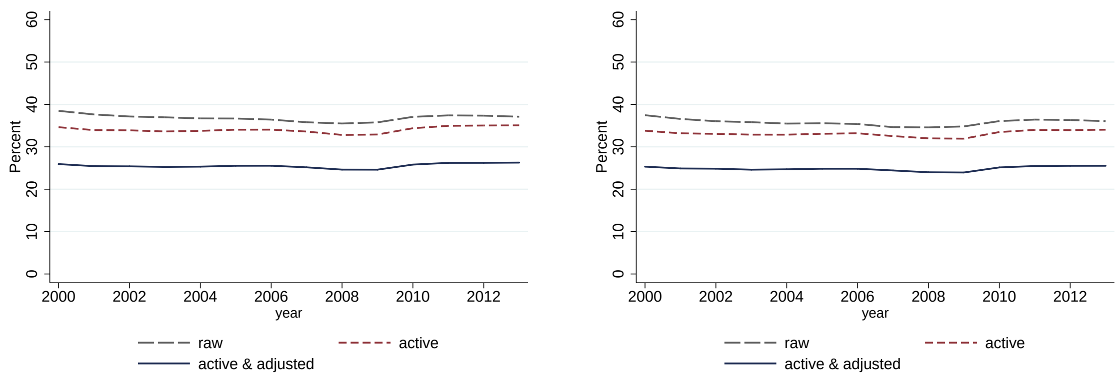
3. The third version (labeled "active & adjusted" in the figures) sums Compustat sums adjusted (by a factor 0.75) employment and adjusted (by a factor 0.79) revenue across all actively traded listed firms and divides it by total BDS employment and BEA gross output.

Figure 2.1 reports the contribution of listed firms to private sector employment. The left panel depicts the contribution of listed firms to total private sector employment and the right panel depicts the contribution of non-FIRE listed firms to non-FIRE private sector employment. Note first that in both the left and right panels the contribution has remained quite stable over the entire period 2000-2013. In the left panel, Compustat firms appear to account for around 37% of private sector employment on average when no adjustments are made for active trading and foreign employment. This average falls to 34% if only actively-traded firms are considered and falls further still to 26% when the domestic employment of actively

[18] The listed firms that are included are obtained by starting with Compustat and 1) keeping one observation per (gvkey, year); 2) dropping financial instruments (ETFs, ADRs, etc)which involves dropping observations with missing NAICS codes and those with NAICS equal to 525; 3) dropping non-U.S. firms, which involves dropping observations with simultaneously missing EIN and state information and those with simultaneously missing EIN and a non-U.S. address; and 5) dropping firms in public administration (NAICS code 92).

traded firms is considered. The right panel focuses on the non-FIRE private sector and here non-FIRE, actively traded listed firms account for around 25% of annual non-FIRE private sector employment.

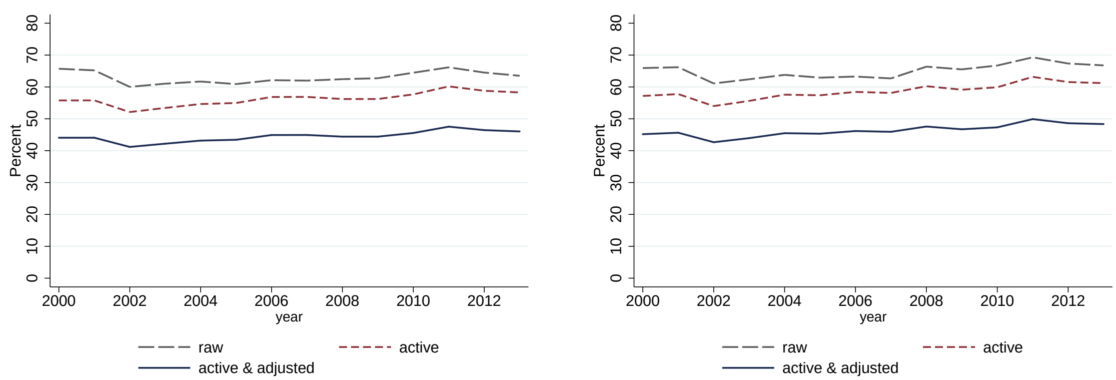
Figure 2.1: Employment: % of Private Sector (left) and non-FIRE (right)



Notes: The left figure plots the contribution of listed firms to private sector employment. The right figure plots the contribution of non-FIRE listed firms to non-FIRE private sector employment. Listed firm employment is obtained from Compustat (revt variable) and private sector employment is obtained from the Census Bureau's BDS tables. In each figure the dashed grey line depicts the raw Compustat employment for listed firms over BDS employment; the dashed red line depicts the raw Compustat employment for actively traded listed firms over BDS employment; and the solid blue line depicts the adjusted (by a factor of 0.75) Compustat employment for actively traded listed firms over gross BDS employment.

Figure 2.2 reports the contribution of listed firms to private sector gross output. The left panel depicts the contribution of listed firms to total private sector gross output and the right panel depicts the contribution of non-FIRE listed firms to non-FIRE private sector gross output. Similar to the employment contribution depicted in the previous figure, in both the left and right panels the contribution of listed firms is fairly stable over time. In the left panel, Compustat firms appear to account for around 63% of private sector gross output on average when no adjustments are made for active trading and foreign employment. This average falls to 56% if only actively-traded firms are considered and falls further still to 44% when the domestic gross output of actively traded firms is considered. The right panel focuses on the non-FIRE private sector and here non-FIRE, actively traded listed firms account for around 46% of annual non-FIRE private sector gross output. Both figures confirm that publicly-traded firms account for an important share of the U.S. economy, but that privately-held firms account for the majority of employment (74%) and gross output (56%).

Figure 2.2: Gross Output: % of Private Sector (left) and non-FIRE (right)



Notes: The left figure plots the contribution of listed firms to private sector gross output. The right figure plots the contribution of non-FIRE listed firms to non-FIRE private sector gross output. Listed firm gross output is obtained from Compustat (revt variable) and private sector gross output is obtained from the BEA's Industry Economic Accounts tables. In each figure the dashed grey line depicts the raw Compustat gross output for listed firms over BEA gross output; the dashed red line depicts the raw Compustat gross output for actively traded listed firms over BEA gross output; and the solid blue line depicts the adjusted (by a factor of 0.79) Compustat gross output for actively traded listed firms over gross BEA output.

The U.S. Census Bureau's LBD has comprehensive data on firm age, employment and, as of recently, revenue, for the entire universe of private firms, but lacks information on firm balance sheets.[19] Thus, to study the financing behavior

[19]While listed firms are legally required to disclose their financial statements, private firms are not. As a result, Compustat, which covers the universe of listed firms in the U.S., has been

of private firms in the U.S. and to verify predictions arising from the literature on financial frictions, we construct a new data set by matching LBD data to Orbis and Compustat using both national firm-level identifiers and an iterative probabilistic name and address matching procedure.[20] From the LBD we obtain information on firm employment, revenue, age, industry, and legal form. Our financial data on listed firms come from Compustat, and our financial data on private firms come from the Orbis database. Both sources contain detailed firm-level balance sheets, income statements, and profit and loss accounts. Orbis is compiled by Bureau van Dijk Electronic Publishing (BvD), a Moody's company. Firm-level administrative data is first collected by local Chambers of Commerce and the business register. The data are then relayed to BvD through 40 different information providers. Although private company reporting is voluntary in the U.S., we show that LOCUS covers more firms than other data sets provided by alternative private vendors.

Research on the financing behavior of private firms has thus far relied on two types of data. The first type includes SDC VentureXpert and CapitalIQ, which focus on private equity issuances and buyouts. As a result, they provide no information on bank debt, and only include the very small sample of firms that raise private equity.[21] The second type of data used to study private firms focuses on very small and very young businesses. The Survey of Small Business Finance (SSBF) is a

extensively relied upon in the literature to study firm financial structure and aggregate implications of financial frictions.

[20]Please refer to appendix B.2 for additional details on the matching procedure.

[21]Bernstein et al. (2016b) uses VentureXpert to analyze how monitoring by venture capitalists affects the innovation and growth of 23,000 venture-backed companies between 1977 and 2006. Davis et al. (2014) use CapitalIQ to track changes in jobs and productivity among a sample of 3,200 firms targeted for leveraged buyouts between 1980 and 2005.

cross-sectional survey conducted in four waves between 1987 and 2003 by the U.S. Federal Reserve. The 2003 survey, for instance, sampled under 5,000 firms from a target population of non-financial firms with less than 500 employees.[22] Similarly, the Kauffman Firm Survey (KFS) focuses on the experience of young firms. It tracks a single cohort of 5,000 firms born in 2004 through 2011.[23] All these data cover select set of private firms that are not representative of the US economy and not span the full firm age and size distributions.

Two exceptions that cover a larger set of private firms over time are the U.S. Census Bureau's Quarterly Financial Report (QFR) survey and Sageworks. The QFR covers the mining, manufacturing, wholesale trade, retail trade and select service sectors. Each quarter it surveys about 4,600 large corporations in these sectors, in addition to a select sample of approximately 5,000 small and medium sized firms in the manufacturing sector. It therefore contains detailed balance sheet information for several thousand private and listed firms across the age and size distributions in the manufacturing sector. Two features distinguish our data LOCUS from the QFR. First, LOCUS encompasses a large sample of small and large firms beyond just the manufacturing sector.[24] Second, the QFR can only be linked to

[22]The SSBF has been used to study borrower-lender relationships as in Petersen and Rajan (2002) and the capital structure decisions of single-owner corporations as in Ang et al. (2010) and Cole (2013). Using the 1993 survey, Berger and Udell (1998) show that due to a high degree of informational opacity, small businesses depend more on funding provided by insiders and receive external funding primarily from private equity and debt markets, as opposed to the public market. By linking loan-level data from the Small Business Administration with the LBD, which covers only very small firms, Brown and Earle (2017) shows that when local credit conditions are weak, access to SBA loans is associated with job growth.

[23]Robb and Robinson (2012) use the survey to document the importance of external financing, such as bank financing, for startups.

[24]Appendix B.1 shows how the QFR coverage compares to the manufacturing sector in the LBD, Compustat and our LOCUS data using both revenue and total assets.

the LBD in Census years to obtain firm employment and age information, which hinders annual analysis and a full assessment of the representativeness of the QFR sample as opposed to LOCUS data.

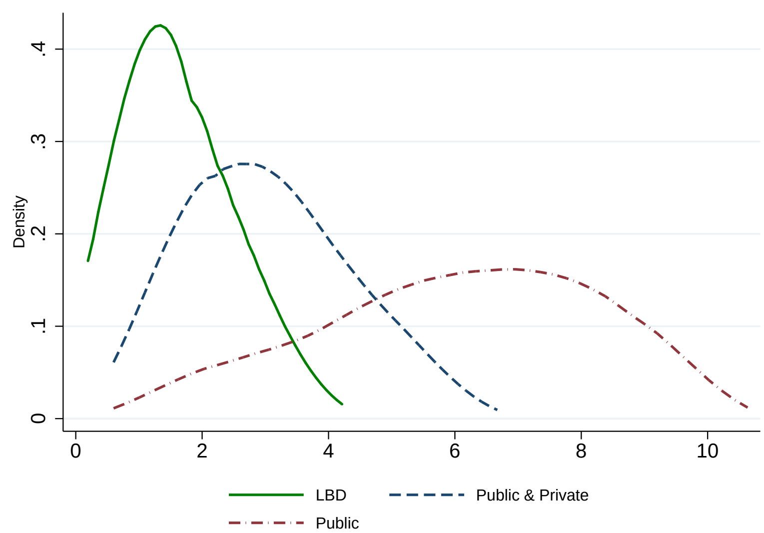
Another proprietary database, Sageworks, contains panel data on over 220,000 listed and private firms. Similar to LOCUS, Sageworks includes information from firm balance sheets and income statements, as well as industry classification and geographic location. In contrast to our LOCUS, Sageworks anonymizes firms (Asker et al., 2015). This feature prevents matching the data to other sources, such as the LBD, that contain information on age and size (employment), both of which are thought to be theoretically and empirically crucial for the relationship between financial constraints and firm dynamics. Additionally, due to inability to match the data to census, a full assessment of how representative firms in the sample are relative of the whole U.S. economy cannot be performed.

To the best of our knowledge, the only other paper that uses ORBIS data for the U.S. is by Nikolov et al. (2017). However these authors do not match the ORBIS data to Census data. They show that private firms in ORBIS have higher leverage relative to the listed firms in Compustat, and are more profitable.

2.3.1 LOCUS Data

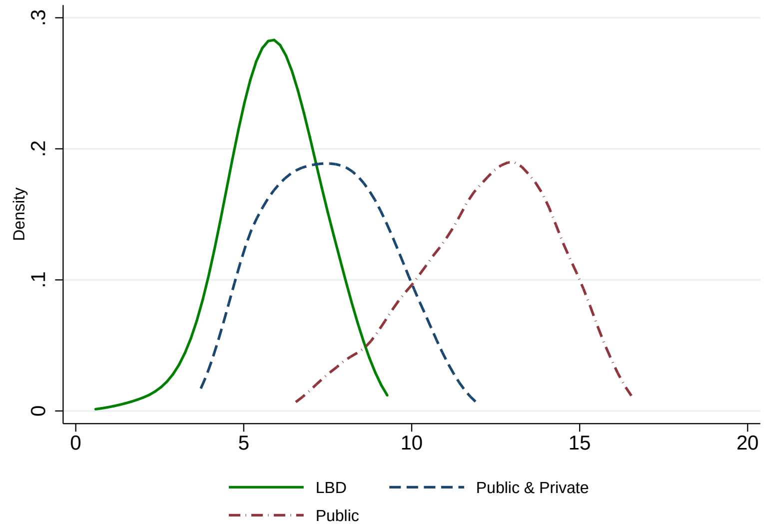
In all, our matched LBD-Orbis-Compustat data on U.S. firms (LOCUS) contains over 180,000 unique firms, 97 percent of which are privately held. Our matched sample covers around 31 percent of U.S. employment, 35 percent of payroll, and 38 percent of U.S. non-farm, non-financial revenue. Privately held firms in our sample consistently account for about 10 percent of the U.S. economy. What is perhaps most striking is how vastly different listed and private firms are. On average, listed firms in our sample have 34 times larger employment (6,200 employees versus 170 employees) and 64 times higher revenue ($293 million versus $7.7 million) than privately held firms in our sample.

Figure 2.3: Comparison of Employment Distributions: LBD, LOCUS & Compustat



Notes: This figure compares the distribution of firm-level employment, obtained from the LBD, among non-financial employer businesses in 2010 that are in LOCUS (contains both private and listed firms), Compustat (listed firms only), and LBD. The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements

Figure 2.4: Comparison of Revenue Distributions: LBD, LOCUS & Compustat



Notes: This figure compares the distribution of firm-level revenue, obtained from the revenue-enhanced LBD, among non-financial employer businesses in 2010 that are in LOCUS (contains both private and listed firms), Compustat (listed firms only), and LBD. The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements

Using employment from LBD and revenue from the revenue-enhanced LBD, figures 2.3 and 2.4 show that our LOCUS data vastly improve the coverage of small and medium sized firms both in terms of employment and revenue relative to the sample of listed (Compustat) firms on which the finance and macro-finance literatures are built. Figures 2.3 and 2.4 also illustrate that our LOCUS data is not representative of the whole U.S. economy. The average employment in LOCUS is 525 versus just 20 in the LBD; and the average age is 21 in LOCUS versus 11 in the LBD. Additionally, we determine that LOCUS firms have higher employment growth rates, are more likely to own multiple establishments, and are more likely to be nonprofits than firms in the LBD. This selection is driven by the fact that our sample contains only privately-held firms that report their financials. The non-representativeness of LOCUS is a concern because we believe that firm financing decisions are influenced by factors such as age, size, growth and legal form. If we naively run regressions using the raw, unweighted LOCUS data, we will misrepresent the strength of the relationship between leverage and firm characteristics such as age and size for the average firm in the economy because the average firm in our raw data is older, larger and grows faster than the average firm in the U.S. economy.

We are able to address this selection head-on because we matched Orbis to the LBD, which contains private firms spanning the entire firm age and size distributions. To do so, we run a series of logistic regressions similar to Haltiwanger et al. (2017) for private firms.[25] Our dependent variable is reporting status and is equal to one for the firm-year observations in LOCUS. To account for the possibility that selection into our matched data varies for firms continuing, entering and exiting the universe of employer-businesses, we estimate separate models for each of these categories. Our regressors are firm employment ($log(emp_i)$), age (age_i), indicator for firms 16 years or older ($D16_i$), employment growth rate (EG_i, 7 categories) for firm i, and a series of fixed effects for 3-digit NAICS industry (ind), multi-unit status (mu), and legal form (lfo, 3 categories).[26] The models we estimate in each year 2005 through 2012 for continuers, entrants and exiters are specified below:

[25] We exclude listed firms from the logistic regressions and assign them a weight of one in our subsequent analysis because they are required to report financials. As a result, LOCUS include all identifiable listed firms in the LBD.

[26] Legal form is divided into three categories – 1) corporation, 2) sole-proprietorship, partnership, and S-corporation, and 3) non-profits and other legal forms.

1. **Employment continuers:**

$$R_{it} = \alpha + \gamma_1 log(emp_i) + \gamma_2 age_i + \gamma_3 D16_i + \gamma_4 EG_i + ind + mu + lfo + \varepsilon_i \quad (2.3)$$

2. **Employment births:**

$$R_{it} = \alpha + \beta_1 ln(emp_i) + ind + mu + lfo + \varepsilon_i \quad (2.4)$$

3. **Deaths**

$$R_{it} = \alpha + \delta_1 log(emp_i) + \delta_2 age_i + \delta_3 D16_i + ind + mu + lfo + \varepsilon_i \quad (2.5)$$

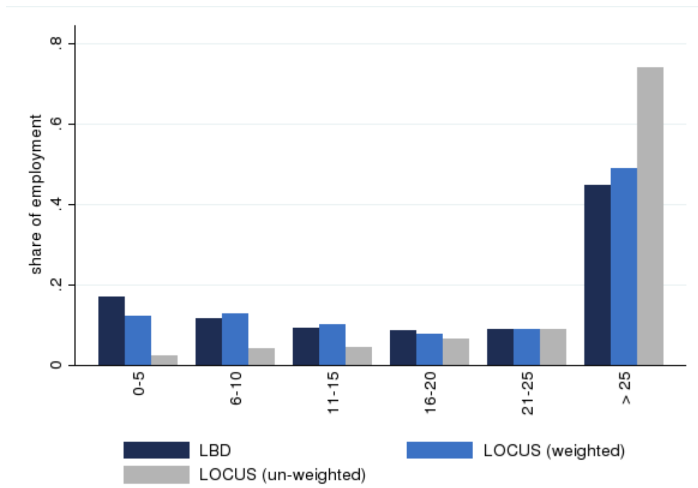
We use the resulting predicted values to construct propensity scores, which we use as weights in the remainder of our analysis. As figures 2.5 through 2.7 and tables 2.1 and 2.2 show, this approach substantially decreases the observable differences between financial reporting and non-reporting privately-held firms once weights are applied.[27] Most noticeably, the weights reduce the over-representation of old, large and multi-unit firms in the unweighted LOCUS data. The approach also addresses the over-representation of non-profit firms, which we expect make different financing decisions than sole-proprietorships, partnerships and corporations.

In table 2.3, we compare the weighted means and standard deviations of key variables for the public and private firms in LOCUS. In constructing our analysis data, we winsorize all financial variables – collateral, profitability, equity over total assets and all leverage variables – at the 1st and 99th percentiles. Listed firms are 62 times larger than private ones and twice as old. Listed firms also are more profitable, and have higher collateral, total leverage and financial leverage. When we decompose leverage into short-term and long-term, private firms have higher short-

[27] In the figures the height of each bar and in the tables the share reported is the share of each sample employment accounted for by each group.

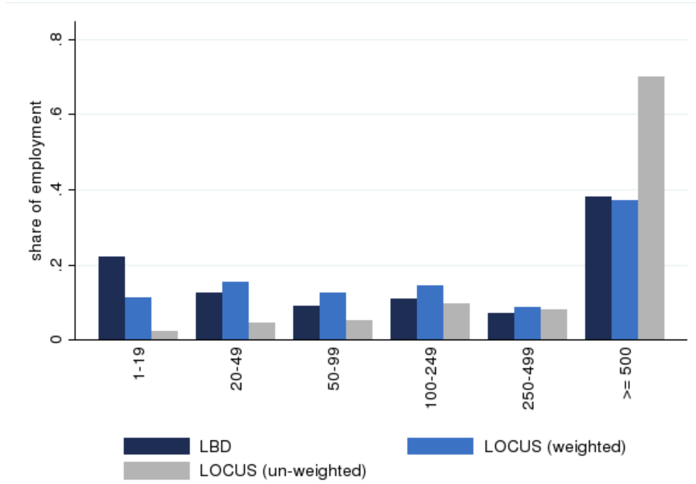
term leverage, while public firms have higher long-term leverage. Private firms also have higher equity over total assets, could reflect their higher reliance on internal equity relative to listed firms.

Figure 2.5: Comparison of Firm Age Distributions (% of emp)



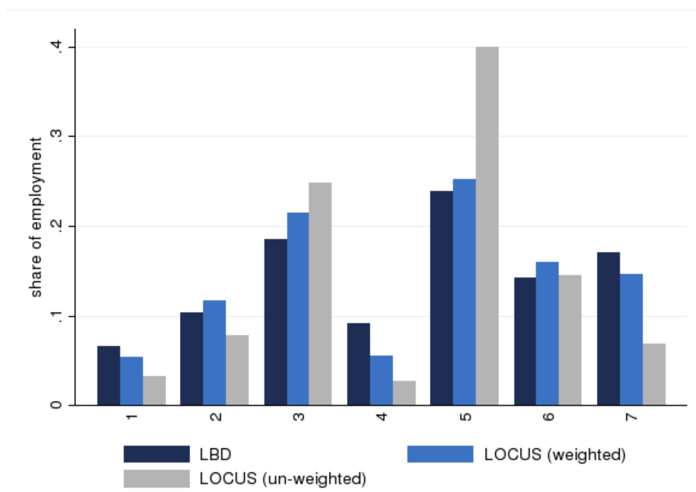
Notes: This figure compares the share of sample firm-level employment accounted for by each age group. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of private firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Figure 2.6: Comparison of Firm Employment Distributions (% of emp)



Notes: This figure compares the share of sample firm-level employment accounted for by each size group. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of private firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Figure 2.7: Comparison Firm Employment Growth Distributions (% of emp)



Notes: This figure compares the share of sample firm-level employment accounted for by each employment growth group. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of private firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Table 2.1: Comparison of Multi-unit Status Distributions (% of emp)

	LOCUS (unweighted)	LOCUS (weighted)	LBD
Single-unit	20.73%	46.09%	53.93%
Multi-unit	79.27%	53.91%	46.07%

Notes: This table compares the fraction of sample firm-level employment accounted for by single- and multi-unit firms. Each column represents a different sample. The first column represents all private, non-financial employer businesses in the LBD. The second column represents the weighted LOCUS sample of private firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Table 2.2: Comparison of Legal Form Distributions (% of emp)

	LOCUS (unweighted)	LOCUS (weighted)	LBD
Corp.	42.29%	46.22%	47.31
S-Corp., Sole-prop. & Part.	12.41%	43.71%	36.47
Other	45.3%	10.08%	16.22

Notes: This table compares the fraction of sample firm-level employment accounted for by each legal form group. Each column represents a different sample. The first column represents all private, non-financial employer businesses in the LBD. The second column represents the weighted LOCUS sample of private firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Table 2.3: Summary Statistics table

	Private		Public	
	mean	stdev	mean	stdev
employment	100		6,200	
age	11		24	
log(employment)	1.8	1.6	6.3	2.4
log(age)	1.9	1.2	3.0	0.7
collateral	0.17	0.24	0.24	0.23
profitability	0.13	0.40	0.22	0.34
total leverage	0.46	0.38	0.56	0.36
financial leverage	0.16	0.24	0.21	0.24
short-term leverage	0.04	0.11	0.03	0.08
long-term leverage	0.12	0.22	0.18	0.21
equity/total assets	0.48	0.38	0.44	0.36

Notes: This table compares the mean and standard deviation of key variables for private and public firms. The means and standard deviations are weighted, where the weights are derived from estimating equations (3) through (5). Employment measures firm-level total employment. Age measures the firm age. Collateral is measured as tangible fixed assets over total assets. Profitability is net income over total assets. Total leverage is total liabilities over total assets. Financial leverage is short-term debt plus long-term debt over total assets. Short-term leverage is short-term debt over total assets. Long-term leverage is long-term loans over total assets. Equity/total assets is total shareholder funds over total assets.

2.4 Empirical Methodology and Results

Now that we have accounted for selection and reweighed observations in LOCUS, we can proceed with a standard leverage regression of the form:

$$\begin{aligned} LEV_{it} = &\alpha + (\omega_s \times \lambda_t) + \beta_1 \log(EMP_{it}) + \beta_2 AGE_{it} + \beta_3 COLLAT_{it} + \\ &\beta_4 PROFIT_{it} + \beta_5 PROD_{it} + \epsilon_{it} \end{aligned} \tag{2.6}$$

where i is the firm and t is time, measured in years. $(\omega_s \times \lambda_t)$ are sector×year fixed effects, where sector is at the 3-digit level. These fixed effects will account for any time varying sectoral selection effects. Notice that this regression identifies from between firm variation since we do not include firm fixed effects. Inclusion of these fixed effects will render the firm age variable irrelevant since its effect will be absorbed by firm fixed effects and time dummies. Since we are interested in the effect of firm age we will run this regression first and afterwards we drop firm age and introduce firm fixed effects and run a panel version of this regression that identifies from within variation.

The above regression is a standard firm leverage regression with firm collateral $(COLLAT_{it})$ and profitability $(PROFIT_{it})$, where we add $log(EMP_{it})$ and age (AGE_{it}) as regressors to capture life-cycle characteristics of firms as determinants of firms leverage. The corporate finance literature also controls for size but mostly using log(assets) as a proxy for size. Given the valuation effects, employment is a more appropriate measure of size since book value of assets will not reflect true size and market value of assets may not reflect true firm growth. The literature also uses cash flow and Tobin's Q as measures of productivity and growth potential. Adding cash flow does not change any of our results. Since 97 percent of our sample is composed of private firms we will not have a Tobin's Q measure. Instead, we use labor productivity $(PROD_{it})$ to control for growth potential.

We focus on three standard measures of leverage as dependent variables: financial debt, short-term debt and long-term debt, each divided by total assets. Both collateral, and profitability are also normalized by assets. In particular, we construct tangible fixed assets to total assets ratio for collateral and net income to total assets ratio for profitability.[28]

We run regressions separately for listed and private firms. As shown in table 2.4, among both listed and private firms collateral is positively related to leverage and profitability is negatively related. These results mimic the results in the previous literature. The only exception is the negative sign on collateral for the private firms' short-term borrowing. This is due to a compositional effect. Total leverage for private firms, measured as financial debt to total assets, is positively related to collateral. What may drive the negative coefficient for short-term borrowing is private firms with a lot of collateral switching from short to long term debt.

The new results here are on firm size and age. As previously mentioned, models of financial frictions generally focus only on short-term debt, so let us distinguish between total, short-term and long-term leverage in discussing our results. We find that firm size, measured as log employment, is positively correlated with firm leverage for private firms for all forms of debt. A one standard deviation increase in size is associated with a 24% rise in overall leverage, a 37% rise in short-term leverage, and a 19% rise in long-term leverage. In contrast, public firms' size is negatively correlated with leverage based on short-term debt. In fact, a one standard deviation increase in size is associated with a 13% decline in short-term leverage among public firms.

If we focused on only the listed firms, we would conclude that our results

[28]profits to total assets is the standard measurue of profitability, but the ORBIS data contains many missing records for profits. Net income over total assets is used instead and for the subsample for which both profits and net income is available, we verify that there is a high correlation between profits over total assets and net income over total assets.

Table 2.4: Leverage Regressions for Private & Listed Firms (2005-2012)

	(FD/TA_{it})		(STL/TA_{it})		(LTL/TA_{it})	
	Listed	Private	Listed	Private	Listed	Private
$\log(EMP_{it})$	0.0178***	0.0281***	-0.0014***	0.0117***	0.0195***	0.0167***
	(0.0008)	(0.0007)	(0.0003)	(0.0003)	(0.0007)	(0.0006)
AGE_{it}	0.0007***	-0.0024***	0.0001	-0.0004***	0.0006***	-0.0019***
	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0002)	(0.0001)
$COLLAT_{it}$	0.2321***	0.1861***	0.0265***	-0.0296***	0.2023***	0.2118***
	(0.0112)	(0.0049)	(0.0043)	(0.0021)	(0.0102)	(0.0045)
$PROFIT_{it}$	-0.1928***	-0.0702***	-0.0688***	-0.0290***	-0.1178***	-0.0402***
	(0.0090)	(0.0037)	(0.0044)	(0.0019)	(0.0076)	(0.0030)
$PROD_{it}$	0.0061***	0.0087***	0.0009	0.0088***	0.0053***	-0.0000
	(0.0020)	(0.0011)	(0.0007)	(0.0006)	(0.0018)	(0.0009)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Wgts (logit)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,000	320,000	20,000	320,000	20,000	320,000
R2	0.2299	0.1525	0.1164	0.0882	0.2275	0.1523

Notes: We consider unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variables are financial debt/total assets (FD/TA_{it}) in the first two columns, short-term debt/total assets (STL/TA_{it}) in the next two columns, and long-term loans/total assets (LTL/TA_{it}) in the last two columns. The main regressors are $\log(EMP_{it})$ to measure firm size; AGE_{it} to measure firm age; $COLLAT_{it}$ to measure tangible fixed assets over total assets; $PROFIT_{it}$ to measure net income over total assets; and $PROD_{it}$ to measure log labor productivity. All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 2.3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

contradict the existing financial frictions literature since this literature (the papers with firm heterogeneity) predicts small firms have lower short-term leverage and larger firms have higher short-term leverage. But private firms, which account for over 60 percent of the economy, tell a different story. The positive correlation between leverage and size supports models featuring decreasing returns to scale and models with explicit heterogeneity in borrowing constraints as a function of size and contradicts models featuring constant returns to scale and a standard borrowing constraint, which predict no relationship between size and leverage. We interpret our finding as showing that size is a measure of financial constraints for private firms but not for listed ones since small private firms cannot borrow short-term while small listed firms can borrow short-term.

Turning to firm age, we find that it plays no significant role for public firms' short-term leverage and a slightly positive role in long-term leverage, which is inconsistent with the theoretical literature predicting a negative relationship. A one standard deviation increase in listed firm age is associated with roughly a 3% rise in long-term leverage. Here again, the experience of private firms is crucial. Private firms borrow more and have higher leverage when they are young. The relationship negative relationship is particularly strong for long-term leverage. A one standard deviation increase in age is associated with about a 12% decline in short-term leverage and a 20% decline in long-term leverage. This is consistent with financial frictions models, which predict, conditional on size, that firms pay down long-term debt as they age. Once more, these results show that age is not a good proxy for financial constraints, but rather size appears to be a more appropriate proxy of such constraints.

We now verify whether our firm size results hold beyond the cross-sectional setting. To do so, we drop age as a regressor, lag all regressors by one period, and introduce firm fixed-effects. That is we run:

$$\begin{aligned} LEV_{it} =& \alpha_i + (\omega_s \times \lambda_t) + \beta_1 \log(EMP_{it-1}) + +\beta_2 COLLAT_{it-1} + \\ & \beta_3 PROFIT_{it-1} + \beta_4 PROD_{it-1} + \epsilon_{it} \end{aligned} \tag{2.7}$$

We focus on a balanced sub-sample of firms for which we have data over the period 2005 through 2011, and run regressions separately for private and listed firms.[29] From the theoretical financial frictions literature, we would anticipate that leverage rises as firms grow due to loosening financial constraints. Since these models primarily focus on short-term lending, we are particularly interested in the relationship between short-term leverage and size. As table 2.5 shows, we do find that leverage and employment are positively related in a longitudinal panel setting. This finding is noteworthy since in the leverage regression upon inclusion of fixed effects, no determinant remains significant in general. As expected, in our case, results are driven by private firms, which are subject to more financial frictions than listed firms, and short-term leverage, which is precisely the focus of financial frictions models.

[29] Orbis coverage of firms in 2012 is limited because it is the end of the data collection period and there are reporting and data gathering lags. We therefore restrict ourselves to the period 2005–2011 in constructing our balanced sample.

Table 2.5: Balanced Panel (2005-2011)

	(Listed)			(Private)		
	FD/TA_{it}	STL/TA_{it}	LTL/TA_{it}	FD/TA_{it}	STL/TA_{it}	LTL/TA_{it}
$\log(EMP_{it-1})$	0.0072	0.0024	0.0025	0.0101	0.0066^{**}	0.0027
	(0.0057)	(0.0024)	(0.0051)	(0.0069)	(0.0033)	(0.0061)
$COLLAT_{it-1}$	0.1199^{***}	0.0097	0.1134^{***}	0.0463^{***}	-0.0019	0.0495^{***}
	(0.0344)	(0.0156)	(0.0333)	(0.0141)	(0.0101)	(0.0148)
$PROFIT_{it-1}$	-0.0516^{***}	-0.0230^{***}	-0.0333^{***}	0.0091	-0.0001	0.0123
	(0.0098)	(0.0056)	(0.0105)	(0.0102)	(0.0034)	(0.0097)
$PROD_{it-1}$	-0.0037	-0.0005	-0.0033	-0.0027	0.0017	-0.0039
	(0.0049)	(0.0014)	(0.0047)	(0.0054)	(0.0026)	(0.0048)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Wgts (logit)	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10,000	10,000	10,000	19,000	19,000	17,000
R2	0.8637	0.5542	0.8410	0.7720	0.6271	0.7904

Notes: We consider balanced samples of private and publicly-listed firms separately between the years 2005 and 2011. The dependent variables are financial debt/total assets (FD/TA_{it}), short-term debt/total assets (STL/TA_{it}), and long-term loans/total assets (LTL/TA_{it}) in the last two columns. The main regressors are $\log(EMP_{it-1})$ to measure firm size; $COLLAT_{it-1}$ to measure tangible fixed assets over total assets; $PROFIT_{it-1}$ to measure net income over total assets; and $PROD_{it-1}$ to measure log labor productivity. All regressions include a full set of 3-digit industry-year fixed effects and firm fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 2.3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

2.4.1 Nonlinear Relationships

To explore possible non-linearities in the relationship between leverage, size and age we run a series of quadratic regressions. We run the regression specified in the previous section separately for public and private firms, and introduce a quadratic term for employment (figures 2.8 through 2.10) or age (figures 2.11 through

2.13).[30] Since financial debt is primarily composed of long-term loans financial leverage behaves as long-term leverage does. As a result, we only report figures associated with financial debt over total assets and short-term loans over total assets. We also consider total equity over total assets to get a sense of how firms might be substituting between debt and equity financing.

We run the following regressions to estimate the non-linear relation between size and leverage and age and leverage:

$$\begin{aligned} LEV_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 \log(SIZE_{it}) + \beta_2 \log(SIZE_{it})^2 + \beta_3 AGE_{it} + \\ & \beta_4 COLLAT_{it} + \beta_5 PROFIT_{it} + \beta_6 PROD_{it} + \epsilon_{it} \end{aligned} \tag{2.8}$$

$$\begin{aligned} LEV_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 AGE_{it} + \beta_2 AGE_{it}^2 + \beta_3 \log(SIZE_{it}) + \\ & \beta_4 COLLAT_{it} + \beta_5 PROFIT_{it} + \beta_6 PROD_{it} + \epsilon_{it} \end{aligned} \tag{2.9}$$

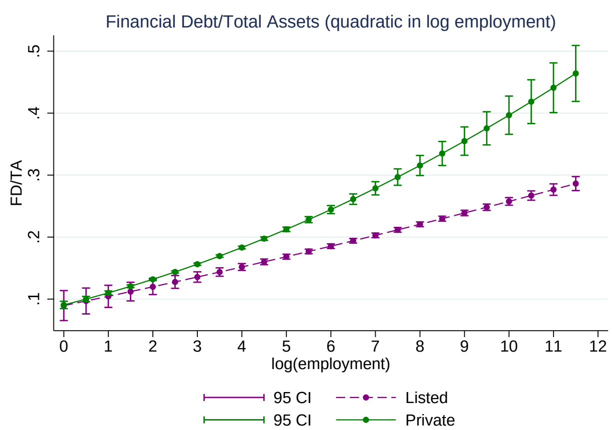
Focusing first on the figures with quadratic employment, we see that size is more strongly positively associated with debt financing (both overall and short-term) among private firms than public ones (figure 2.8 and 2.9). In fact, there is no relation between size and short-term leverage for listed firms. This finding is consistent with private firms facing more financial frictions than listed ones. Note also that there is a logarithmically convex relationship between long-term leverage and size for private firms, but the short-term leverage and size relationship appears more logarithmically concave. Moreover, among private firms there is a strong negative relationship between total equity over total assets and employment (figure 2.10). One interpretation is that as financial constraints ease, private firms choose

[30] Each figure plots the predicted values of the dependent variable as a function of the independent variable of interest (size or age), holding all other variables at their sample means.

debt financing over internal equity.

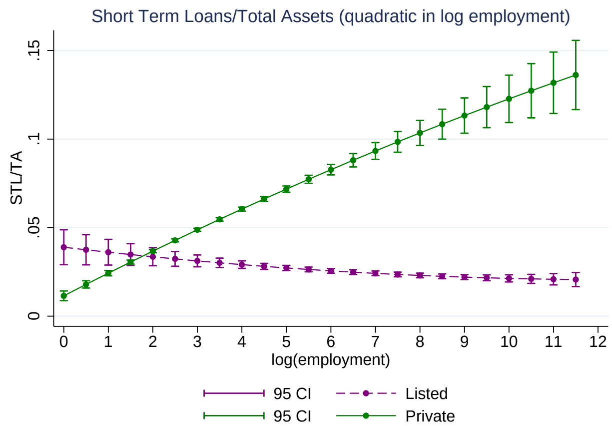
The equity-size relationship has more of an inverted U-shape for public firms. Since these firms have access to external equity via stock issuances, one interpretation is that small and medium sized listed firms complement long-term debt with external equity. As they become larger, they issue less external equity and turn toward long-term debt borrowing.

Figure 2.8: Quadratic Relationship between FD/TA and Size



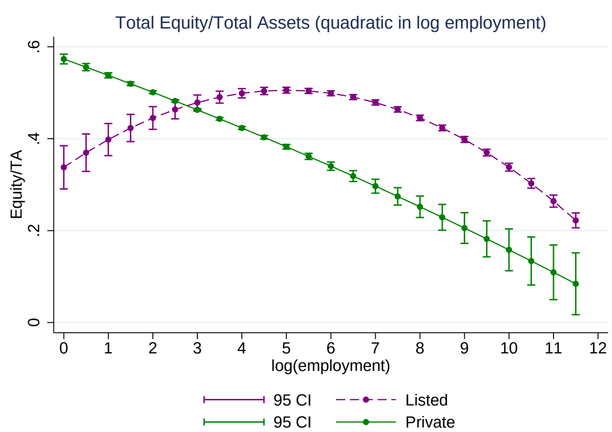
Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is financial debt/total assets. Each line shows the conditional relationship between firm size and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

Figure 2.9: Quadratic Relationship between STL/TA and Size



Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is short-term loans/total assets. Each line shows the conditional relationship between firm size and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

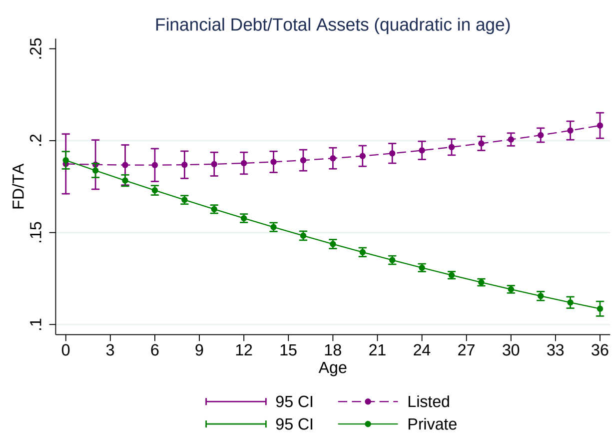
Figure 2.10: Quadratic Relationship between Equity/TA and Size



Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is total equity/total assets, where total equity includes both internal and external equity. Each line shows the conditional relationship between firm size and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

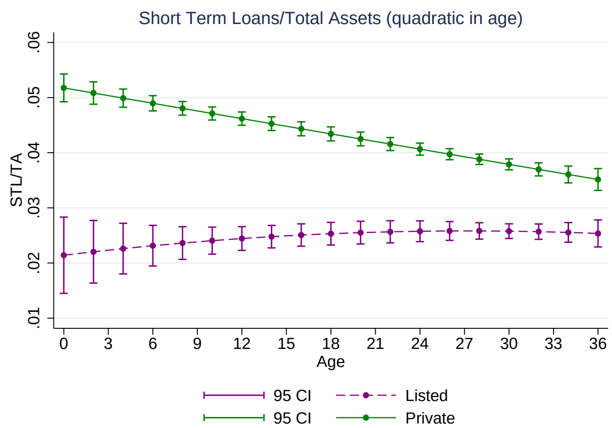
Turning now to figures that are quadratic in age. Private firms appear to draw down short-term leverage as they age, which is consistent with theories in which entrepreneurs borrow to start their businesses and then pay off their loans as they age (figures 2.11 and 2.12). This is consistent with what we see in figure 2.13 where private firms raise internal equity as they age, while paying down their short-term loans. The relationship between age and leverage is far weaker and quite flat among public firms in all measures of leverage. Public firms appear to slightly reduce their equity as they age. This behavior is consistent with large public firms being leveraged in long term debt – as they grow older, they also become larger. Though confidence intervals are not very tight for these relations for listed firms.

Figure 2.11: Quadratic Relationship between FD/TA and Age



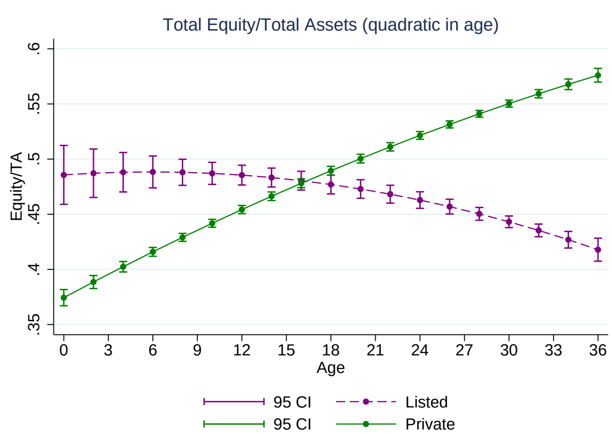
Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is financial debt/total assets. Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age. The figures condition on firm size, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

Figure 2.12: Quadratic Relationship between STL/TA and Age



Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is short-term loans/total assets. Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age. The figures condition on firm size, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

Figure 2.13: Quadratic Relationship between Equity/TA and Age



Notes: Use unbalanced samples of private and public firms between the years 2005 and 2012. The dependent variable is total equity/total assets, where total equity includes both internal and external equity. Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age. The figures condition on firm size, collateral, profitability, labor productivity, and a full set of 3-digit industry-year FE. LOCUS propensity weights are used.

2.4.2 Response to Shocks: Evidence from Great Recession

Since LOCUS spans the Great Recession, we can investigate whether the life-cycle patterns we observe change during the financial shock of 2009–2012. Again, we decompose financial leverage into short-term and long-term leverage in table 2.6. Focusing on the pre-crisis period (2005–2008), we see similar results as before, where the experience of private firms is consistent with financial frictions models with decreasing returns to scale. Larger firms are less financially constrained and therefore have higher leverage. The relationship is stronger for short-term leverage than long-term leverage. A one standard deviation increase in size during this period is associated with a 43% increase in short-term leverage and a 16% increase in long-term leverage. Older firms pay down their long-term debt, resulting in a negative relationship between long-term leverage and age. The relationship is stronger, as predicted in theory, for long-term leverage. A one standard deviation increase in age is associated with a 9% decline in short-term leverage and a 20% decline in long-term leverage. Listed firms are less leveraged in terms of both short-term and long-term debt than private firms. Moreover, since these listed firms are likely less affected by financial frictions their experience is inconsistent with theory. In particular, we do not find a positive relationship between public firms' size and short-term leverage and age is positively correlated with leverage.

Table 2.6: Pooled Regressions: Short-term leverage & Long-term leverage

	(2005-2012)		(2005-2008)		(2009-2012)	
	STL/TA_{it}	LTL/TA_{it}	STL/TA_{it}	LTL/TA_{it}	STL/TA_{it}	LTL/TA_{it}
$\log(EMP_{it})$	0.0117***	0.0167***	0.0158***	0.0176***	0.0085***	0.0160***
	(0.0003)	(0.0006)	(0.0004)	(0.0009)	(0.0005)	(0.0009)
AGE	-0.0004***	-0.0019***	-0.0004***	-0.0026***	-0.0004***	-0.0013***
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
$COLLAT_{it}$	-0.0296***	0.2118***	-0.0335***	0.2425***	-0.0200***	0.1732***
	(0.0021)	(0.0045)	(0.0025)	(0.0062)	(0.0036)	(0.0064)
$PROFIT_{it}$	-0.0290***	-0.0402***	-0.0297***	-0.0402***	-0.0281***	-0.0405***
	(0.0019)	(0.0030)	(0.0020)	(0.0039)	(0.0037)	(0.0045)
$PROD_{it}$	0.0088***	-0.0000	0.0128***	-0.0001	0.0055***	0.0003
	(0.0006)	(0.0009)	(0.0007)	(0.0013)	(0.0009)	(0.0013)
$PUBLIC_i$	-0.0236***	-0.0964***	-0.0211***	-0.1040***	-0.0208***	-0.0702***
	(0.0030)	(0.0065)	(0.0042)	(0.0088)	(0.0043)	(0.0095)
$\log(EMP_{it})$ x $PUBLIC_i$	-0.0129***	0.0004	-0.0169***	-0.0027**	-0.0095***	0.0050***
	(0.0005)	(0.0010)	(0.0006)	(0.0014)	(0.0007)	(0.0014)
AGE_{it} x $PUBLIC_i$	0.0006***	0.0025***	0.0005***	0.0034***	0.0004***	0.0007***
	(0.0001)	(0.0002)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
$COLLAT_{it}$ x $PUBLIC_i$	0.0507***	-0.0081	0.0535***	-0.0594***	0.0445***	0.0481***
	(0.0042)	(0.0093)	(0.0058)	(0.0128)	(0.0061)	(0.0134)
$PROFIT_{it}$ x $PUBLIC_i$	-0.0376***	-0.0782***	-0.0346***	-0.0800***	-0.0408***	-0.0694***
	(0.0048)	(0.0082)	(0.0062)	(0.0111)	(0.0076)	(0.0119)
$PROD_{it}$ x $PUBLIC_i$	-0.0114***	0.0041**	-0.0133***	0.0033	-0.0106***	0.0038
	(0.0008)	(0.0019)	(0.0011)	(0.0025)	(0.0012)	(0.0028)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	340,000	340,000	160,000	160,000	180,000	180,000
R2	0.0882	0.1523	0.0864	0.1478	0.0931	0.1307

Notes: We consider a pooled unbalanced samples of private and publicly-listed firms between the periods 2005-2012 in the first two columns, 2005-2008 in the next two columns and 2009-2012 in the last two columns. The dependent variables are short-term loans/total assets and long-term debt/total assets. The main regressors are firm size, firm age, collateral, profitability, labor productivity, a publicly-listed dummy, and a full set of interaction terms. The coefficients on the uninteracted regressors denotes the marginal effect of each regressor on leverage among the privately-held firms. The interacted terms indicated the extra boost (or dampening) effect of being publicly traded. All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 2.3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

However, during the crisis (2009–2012), when both public and private firms are likely to be affected by financial frictions the differences between them are dampened. Listed firms remain less leveraged than private firms. Older public firms pay down their long-term leverage, similar to private firms. A one standard deviation increase in age is associated with 15% decline in short-term leverage among private firms and a 2% decline among listed firms. Even during the crisis listed firms remain relatively less financially constrained than private firms since there is even a negative relationship between size and short-term leverage. A one standard deviation increase in size among private firms is associated with a 32% increase in short-term leverage and a 9% decline among public firms.

2.4.3 Nonlinear Relationships During the Great Recession

In the previous sections we argued that size (employment) is an informative correlate of financial constraints. We found that listed firms are less affected by financial constraints than private firms both before and after the financial crisis. In this section, we dig further into the relationship between leverage and size during the Great Recession.

In figures 2.14 and 2.15 we plot the quadratic relationship between size and short-term leverage for private (figure 2.14) and listed (figure 2.15) firms before the crisis in 2006 and during the crisis in 2009. To generate this figure and the next, we run a regression of short-term leverage on size, size squared and industry fixed effects for private firms (figure 2.14) and listed firms (figure 2.15) separately for 2006 and 2009.

$$STLEV_i = \alpha + \omega_s + \beta_1 \log(SIZE_i) + \beta_2 \log(SIZE_i)^2 + \epsilon_i \tag{2.10}$$

where $STLEV_i$ is short-term debt over total assets, ω_s captures industry fixed effects, and $SIZE_i$ is measured by either employment or total assets. This specification is a close empirical counterpart to the size-dependent collateral constraints arising in macroeconomic models with financial frictions where constraints are a function of firm size or models with decreasing returns to scale. [31]

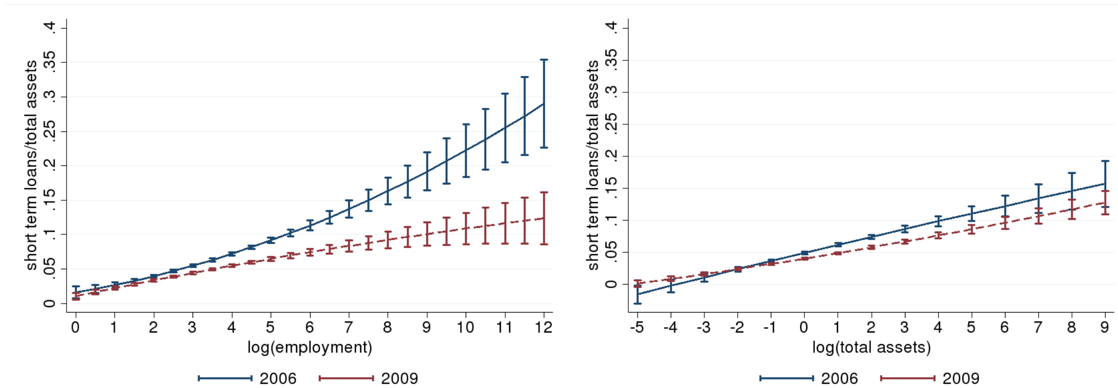
In the left panel of figure 2.14, we measure size by employment and in the right panel by total assets. Consistent with our prior results, for private firms there is a positive correlation between size (employment and total assets) and short-term leverage in both years. The relationship becomes flatter during the crisis (2009). When size is measured by employment, the relationship between size and leverage is significantly weaker in 2009 than it was in 2006. The pattern is consistent with private firms becoming more financially constrained in 2009 or demanding less bank financing during this period.

In contrast, figure 2.15 shows that for listed firms the relationship between leverage and size is negative in both 2006 and 2009 and when size is measured by employment and total assets. Moreover, we do not observe a significant difference in the size-leverage relationship in 2006 and 2009. These results are consistent with our previously reported regression results and suggest that listed firms are less affected

[31] In section B.3 of the appendix, figures B.3 and B.4 show the results when, in addition to industry fixed effects, we control for labor productivity, collateral, profitability and age. The figures are qualitatively consistent with the figures presented in the main text without the additional controls.

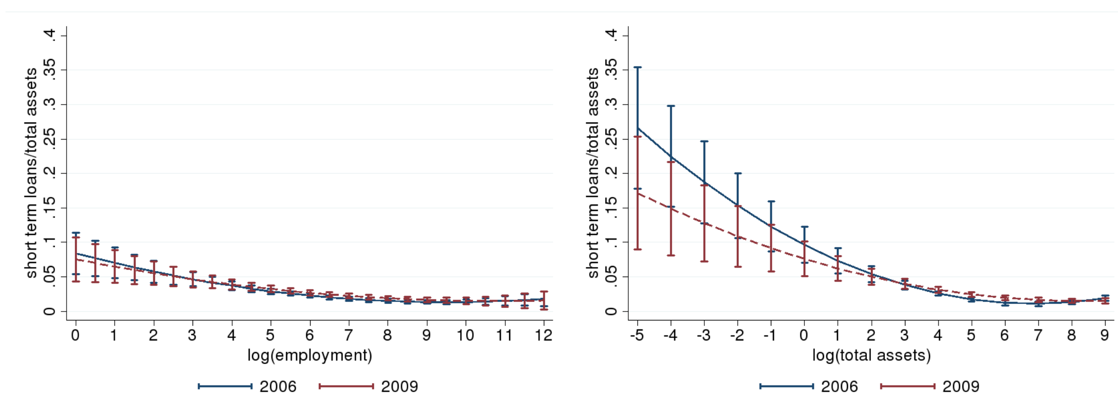
by financial frictions both before and during the Great Recession. The results also highlight the importance of data on private firms since not only is the relationship between leverage and size weaker for public firms, it also has the opposite sign.

Figure 2.14: Relationship b/w ST leverage and size for private firms (2006 & 2009)



Notes: Use unbalanced sample of private firms for 2006 and 2009. The dep. variable is short-term leverage. Each line shows the relationship between leverage, size (measured by employment in the left panel and total assets in the right figure) and size squared, controlling only for a full set of 3-digit industry FE. LOCUS propensity weights are used.

Figure 2.15: Relationship b/w ST leverage and size for public firms (2006 & 2009)



Notes: Use unbalanced sample of public firms for 2006 and 2009. The dependent variable is short-term leverage. Each line shows the between leverage, size (measured by employment in the left panel and total assets in the right figure) and size squared, controlling only for a full set of 3-digit industry FE. LOCUS propensity weights are used.

2.4.4 Firm Growth During Normal Times and the Great Recession

These results have important implications for the aggregate economy as long as financial frictions affect real outcomes. In this section, we complement our analysis of the relationship between leverage and firm life-cycle characteristics with an analysis of the relationship between leverage and revenue growth. We first consider the following cross-sectional regression (first three columns of table 2.7).

$$\begin{aligned} RG_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 STLEV_{it-1} + \beta_2 (STLEV_{it-1} \times PUBLIC_i) + \\ & \beta_3 (STLEV_{it-1} \times CRISIS_t) + \beta_4 (STLEV_{it-1} \times PUBLIC_i \times CRISIS_t) + \\ & \mathbf{\Gamma}' Z_{it-1} + \epsilon_{it} \end{aligned} \tag{2.11}$$

where RG is revenue growth, measured as $\frac{REV_{it} - REV_{it-1}}{0.5(REV_{it} + REV_{it-1})}$; $(\omega_s \times \lambda_t)$ captures industry-year fixed effects and $STLEV_{it}$ is short-term debt over total assets. $STLEV_{it}$ is interacted with a dummy equal to one if the firm is publicly-listed ($PUBLIC_i$), a dummy equal to one during the financial crisis (2008 and 2009), and both $PUBLIC_i$ and $CRISIS_t$. Z_{it-1} includes firm age (AGE_{it-1}), log revenue ($\log(REV_{it-1})$), profitability ($PROFIT_{it-1}$), and labor productivity ($PROD_{it-1}$). Each of these additional controls is included on its own, interacted with $PUBLIC_i$, interacted with $CRISIS_t$ and interacted with both $PUBLIC_i$ and $CRISIS_t$. In addition to the cross-sectional specification, we also report results using firm fixed effects (last three columns of table 2.7):

$$
\begin{aligned}
RG_{it} = & \alpha_i + (\omega_s \times \lambda_t) + \beta_1 STLEV_{it-1} + \beta_2 (STLEV_{it-1} \times PUBLIC_i) + \\
& \beta_3 (STLEV_{it-1} \times CRISIS_t) + \beta_4 (STLEV_{it-1} \times PUBLIC_i \times CRISIS_t) + \\
& \mathbf{\Gamma}' Z_{it-1} + \epsilon_{it}
\end{aligned}
\tag{2.12}
$$

Table 2.7 reports the results of the cross-sectional specification in the first three columns and the firm fixed effects specification in the last three columns. The first and fourth columns do not include any interaction terms and show that there exists a positive relationship between short-term borrowing and revenue growth, though the significance is weaker in column (4) with firm fixed effects. The fifth and sixth columns explain why this is the case. The second and fifth columns introduce interactions with $PUBLIC_i$ and highlight that the positive relationship between firm growth and leverage is driven entirely by private firms. In fact, the relationship between short-term leverage and growth is negative for listed firms. This negative relationship may be indicative of listed firms relying more heavily on different forms of financing, such as long-term debt, than private firms. In columns three and six, we focus on the crisis period ($CRISIS_t$). The negative relationship between leverage and growth for public firms is independent of crisis. The relationship between short-term leverage and growth also does not change in the cross section of *private* firms but becomes weaker during crisis in the firm fixed effect specification for the private firms. When we calculate the total effect of leverage on growth for private firms during crisis, we find that this effect is basically insignificant. We observe no difference between private and public firms during crisis periods in terms of their growth-leverage relationship as shown with triple interaction in columns three and six.

Our analysis of the relationship between revenue growth and leverage further highlights the importance of using data on private firms since the relationship between growth and short-term leverage differs substantially between private and listed firms. Overall our empirical analysis using LOCUS dataset indicates that to obtain a more complete picture of the implications of financial frictions for the broader economy, it is important to take into account, in addition to public firms, private firms that account for over half of the employment and revenue in the U.S. economy. The findings also caution testing of theories incorporating financial frictions at the firm level using data on publicly traded firms only. The stark differences in the life-cycle leverage patterns exhibited by public versus private firms point to a need for a more nuanced approach to modeling financial frictions for these two types of firms. In addition, the differences between the two groups of firms matter for macro models that study the interaction between financial frictions and aggregate shocks. Both groups are clearly large enough to be influential in macro outcomes, and the differential response of the two groups to shocks should be taken into account when studying the consequences of aggregate shocks.

Table 2.7: Growth Regressions

	(1) Growth$_{it}$	(2) Growth$_{it}$	(3) Growth$_{it}$	(4) Growth$_{it}$	(5) Growth$_{it}$	(6) Growth$_{it}$
STLEV$_{t-1}$	0.1013***	0.1023***	0.0829***	0.0524*	0.0530*	0.0802***
	(0.0216)	(0.0216)	(0.0255)	(0.0276)	(0.0277)	(0.0292)
STLEV$_{t-1}$ × PUBLIC$_i$		-0.3588***	-0.3650***		-0.2726***	-0.3546***
		(0.0814)	(0.0968)		(0.0824)	(0.0964)
STLEV$_{t-1}$ × CRISIS$_t$			0.0536			-0.0793**
			(0.0440)			(0.0351)
STLEV$_{t-1}$ × PUBLIC$_i$ × CRISIS$_t$			0.0291			0.2215
			(0.1721)			(0.1575)
log(REV)$_{t-1}$	-0.0122***	-0.0124***	-0.0056*	-0.4923***	-0.4933***	-0.4959***
	(0.0027)	(0.0027)	(0.0031)	(0.0164)	(0.0165)	(0.0159)
log(REV)$_{t-1}$ × PUBLIC$_i$		0.0123***	0.0046		0.1839***	0.1895***
		(0.0033)	(0.0038)		(0.0297)	(0.0296)
log(REV)$_{t-1}$ × CRISIS$_t$			-0.0198***			0.0059
			(0.0057)			(0.0039)
log(REV)$_{t-1}$ × PUBLIC$_i$ × CRISIS$_t$			0.0227***			-0.0027
			(0.0074)			(0.0040)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Weights	Yes	Yes	Yes	Yes	Yes	Yes
Full set of controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	144,000	144,000	144,000	144,000	144,000	144,000
R-sq	0.0759	0.0760	0.0804	0.6140	0.6142	0.6144
private		0.0000	0.0012		0.0563	0.0062
public		0.0009	0.0028		0.0029	0.0025
private-crisis			0.0002			0.9822
public-crisis			0.0834			0.6823

Notes: We consider a pooled unbalanced sample of publicly listed firms between the periods 2005-2012. The dependent variable is the firm-level revenue growth rate. The first three columns are cross-sectional and the last three control for firm-fixed effects. The main regressors are short-term leverage, revenue, firm age, profitability, and labor productivity. All regressors are lagged and interacted with a public dummy, crisis dummy, and the interaction of the two. All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 2.3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively. The last four lines of the table report the p-value of the total effects for: 1) private firms in normal times (private); 2) listed firms in normal times (public); 3) private firms in the financial crisis (private-crisis); and 4) listed firms in the financial crisis (public-crisis).

2.5 Conclusion

We construct a new data set, LOCUS, that provides information on financials of private firms in the U.S. to study the firm life-cycle dynamics of firm financing, and its implications on firm growth and responsiveness to aggregate shocks. To provide a broad picture for both public and private firms, we match financial data for privately-held firms in Orbis and publicly-listed firms in Compustat to U.S. Census Bureau's Longitudinal Business Database. This match allows us to account for selection in Orbis, and to also include administrative data on employment - a key variable that is not available in Orbis.

Our results indicate that, conditional on firm age and other observables that can affect firm borrowing, small private firms may be more financially constrained given the strong positive correlation between firm size and short term leverage, both in cross-section and over time, whereas leverage of public firms is largely independent of their size. The relationship between size and short-term leverage is non-linear and slightly concave for private firms, whereas for public firms it is flat. Firm age, after controlling for firm size and other observables, turns out not to be a proxy for financial constraints, since young firms tend to borrow more and pay down their debt as they grow older. We find that very large public firms stay highly leveraged in terms of long term debt, even when they get older, while private firms switch from debt to equity financing, as they age.

Using Great Recession as an aggregate shock, we show that, the positive and non-linear relationship between size and short-term leverage becomes more linear during the recession, as large private firms reduce their leverage more. For public firms, the relation between short-term leverage and size does not change during the crisis and stays flat. This finding supports our interpretation that public firms are never constrained, while small private firms are constrained during normal times, and large private firms might also get constrained during crisis times. These findings might also have a different interpretation based on demand shocks that can reduce borrowing by firms. It might be the case that demand shocks that are relevant for the period 2007 and after might have a disproportionate effect on larger private firms. We control for firm-level profitability and sector-year fixed effects to account for such shocks though we still cannot rule out fully the effects of firm-level unobserved demand shocks.

The implications of life-cycle leverage on firm growth are as follows. Private firms finance their growth mainly through short-term debt during normal times. During the Great Recession, the strong positive relation between short-term leverage and private firm growth stays in the cross-section but gets weaker during crisis when we use firm fixed effects. If these fixed effects capture unobserved and time invariant firm-level low demand during crisis years, then private firms which entered the crisis with higher short-term leverage grow less during crisis, which might be due to a deleveraging effect. It may also be the case that these firms were affected more from time varying negative demand shocks. Again, for public firms there is no effect of crisis in terms of the relation between leverage and firm growth.

Our results for private firms are consistent with some theories of firm dynamics and financing, whereas the behavior of listed firms is substantially different and cannot be explained by the existing models. Since most of the existing models rely on full firm size distribution, it is not surprising that the results for listed firms do not square with these models. An important implication of our results is that macro-finance models should not be relying *solely* on data moments extracted from listed firm samples for their calibration exercises.

Chapter 3: Sudden Stops, Misallocation and Aggregate Productivity

3.1 Introduction

Over the past 30 years emerging economies have periodically experienced sudden stops, including the Mexican peso crisis in 1995, the East Asian financial crisis in 1997, the Russian default in 1998 and most recently, the Great Recession.[1] All of these events are characterized by large capital outflows and spikes in the real interest rate. During these crises output, investment and productivity fall. For instance, when Russia partially defaulted on its debt in 1998 the credit spreads of the seven largest countries in Latin America rose threefold within a matter of weeks, despite the fact that these countries had few financial or trading ties to Russia. As a result, output in these countries fell by an average of 3.5%, investment by 10% and total factor productivity (TFP) by 4% relative to pre-crisis levels.

The existing small open economy literature cannot fully explain the short-run fluctuations in productivity observed during these episodes.[2] I ask whether fluctuations in the credit spread can simultaneously explain the decline in output,

[1] Calvo et al. (2006) identify sudden stop when the fall in a country's capital flows exceeds two standard deviations from the mean and its country spread (measured by the JP Morgan EMBI spread) rises by more than two standard deviations from the mean.

[2] Neumeyer and Perri (2005), Aguiar and Gopinath (2006), and Fernandez-Villaverde et al. (2011) show how interest rate fluctuations impact output and investment, but cannot explain the fall in productivity unless it is exogenously imposed.

investment and productivity during sudden stops. When the interest rate rises or interest rate volatility increases, firms facing partially irreversible investment and hiring costs become less responsive to their productivity and demand shocks. This fall in responsiveness raises misallocation of resources across firms, which contributes to a fall in aggregate productivity. I explore how much of the decline in productivity observed following shocks to the level and volatility of the interest rate can be explained by this channel.

In order to do so, I focus on the experience of Chile. Using firm-level data, I document that during the 1998 sudden stop the dispersion in the marginal product of capital and labor rose by nearly 8%. This finding is consistent with a rise in resource misallocation wherein firms become less responsive to their productivity shocks due to capital and labor adjustment frictions. The share of firms delaying investment/disinvestment rose from 32% prior to the crisis to 43% by 2000.

Because the direct effect of interest rate fluctuations on dispersion in marginal products and productivity is difficult to identify empirically, I take a structural approach in order to quantify the the contribution of capital and labor adjustment frictions to the fall in productivity when interest rates are high and volatile. I extend a standard heterogeneous firm model with partially irreversible investment and hiring costs, as well as a stochastic interest rate process that is subject to level and volatility shocks.

Consider how investment responds to these shocks. When the interest rate rises some growing firms halt their expansion in anticipation of lower future interest rates; other firms hold on to too much capital because it can only be sold at a fraction of its purchase price and they anticipate wanting to invest in the future when interest rates fall. An increase in interest rate volatility makes firms more uncertain about the costs of financing investment in the short to medium term, since the shocks are only temporary. This uncertainty increases the firm's incentive to delay investment decisions until aggregate conditions become more clear. In both cases resource misallocation rises, which has detrimental effects on aggregate productivity.

I calibrate the model using firm-level data from Chile; subject the economy to shocks to the interest rate; and assess the effect of these shocks on output, investment, hiring, aggregate productivity, and the dispersion of marginal products. Both interest rate level and volatility shocks lead to declines in output, investment, and hiring. These shocks also generate an increase in the dispersion of marginal product of capital and labor, which is consistent with the firm-level data from Chile. The model generates an endogenous fall in aggregate productivity, but the magnitude of the decline is only a small fraction of that observed in the data.

The remainder of the paper is organized into seven sections. Section 3.2 briefly discusses how this paper intersects with the existing literature. Section 3.3 introduces Chile's firm-level data and documents the evolution of the dispersion in marginal products; and presents evidence of adjustment frictions. Section 3.4 briefly discusses the theoretical underpinnings of the adjustment friction channel. Section 3.5 presents the heterogeneous firm model and discusses calibration. Section 3.6 explores how the economy responds to interest rate level and volatility shocks; and section 3.7 concludes.

3.2 Related Literature

This paper belongs at the intersection of the small open economy and misallocation literature. It aims to understand the effect of large fluctuations in the level and volatility of the real interest rate on productivity in emerging economies. Neumeyer and Perri (2005) and Aguiar and Gopinath (2006) are most successful in explaining the impact of interest rate shocks on output, investment and labor when they assume that interest rate fluctuations are induced by exogenous productivity shocks. In these models, when interest rates are uncorrelated with productivity shocks the countercyclicality of interest rates is only half that observed in the data. Yet, Uribe and Yue (2006) find that external conditions, rather than domestic fundamentals, explain 80% of changes in emerging market real interest rates. My contribution to this literature is in showing how interest rate shocks can simultaneously explain the fall in productivity, output, investment, and hiring once the increase in resource misallocation that arises in response to these shocks is taken into account.

My work is not alone in trying to explain how interest rate fluctuations affect productivity. Queralto (2018) and Ates and Saffie (2016) focus on the effect of higher interest rates on firm entry, while Pratap and Urrutia (2012) emphasize resource misallocation across sectors and Meza and Erwan (2007) highlight falling factor utilization. Along with Oberfield (2010), I focus on a complementary channel, capital and labor adjustment frictions. Whereas the firm entry channel generates medium- to long-run fluctuations in productivity, the adjustment frictions channel primarily generates short-run dynamics. Adjustment frictions also imply misallocation of resources across firms within a sector, as opposed to the misallocation of resources between sectors emphasized in Pratap and Urrutia (2012) or the within firm variation arising from utilization emphasized in Meza and Erwan (2007).

The adjustment frictions channel has empirically testable implications for the degree of dispersion in marginal products of capital and labor, which connects my work to the misallocation literature. Hsieh and Klenow (2009) interpret high levels of dispersion in productivity and marginal products as indicative of distortions. As in Bartelsman et al. (2013), I assume dispersion arises from both frictions and distortions, and focus on how much of this dispersion is explained by adjustment frictions alone. Similar to Buera and Moll (2015) and Gopinath et al. (2017) I also emphasize the evolution of productivity and dispersion following an aggregate shock. Whereas Buera and Moll (2015) explore the implications of credit tightening and Gopinath et al. (2017) focus on a permanent fall in the interest rate, I highlight the impact of transitory interest rate fluctuations associated with sudden stops in emerging economies.

My approach in quantifying the effect of interest rate shocks is closely akin to Bloom (2009). I use an industry equilibrium model with risk-neutral firms and labor and capital adjustment frictions and augment it with a stochastic interest rate process. I introduce the insights of Fernandez-Villaverde et al. (2011), who show that periods of high interest rates also feature high interest rate volatility, into a heterogeneous firm model. Doing so allows me to extend the results of Fernandez-Villaverde et al. (2011) by showing how interest rate volatility shocks impact aggregate productivity.

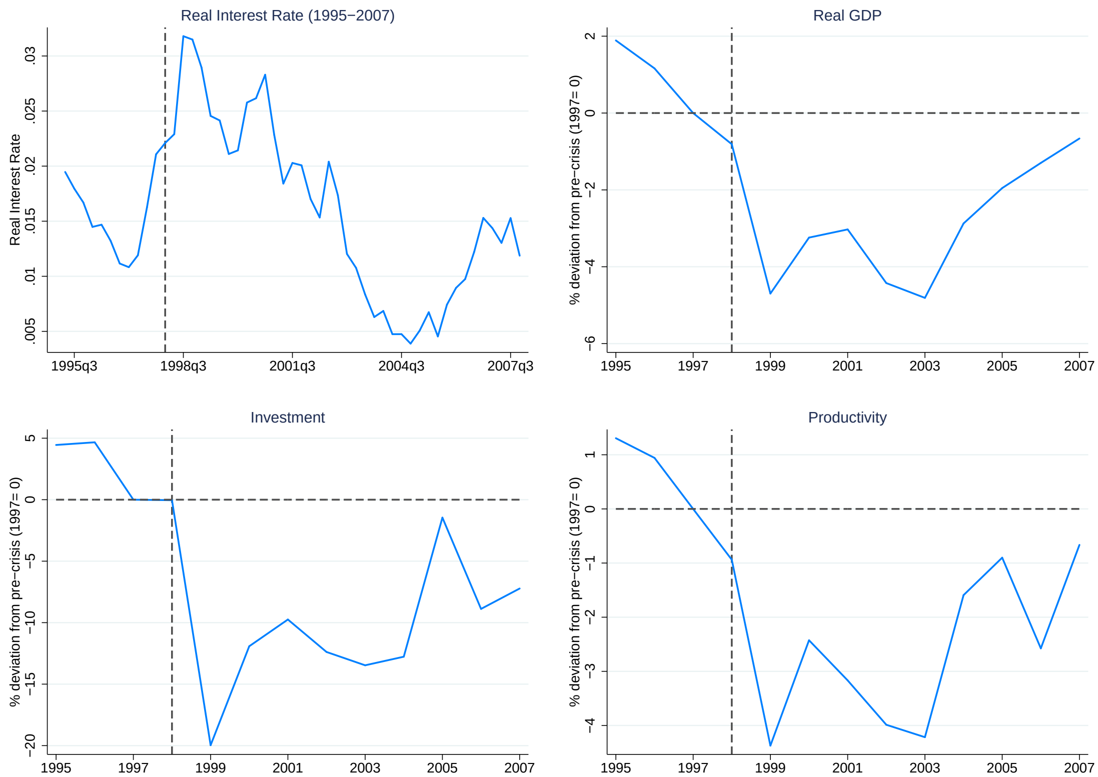
3.3 Evidence of Falling Productivity, Rising Dispersion and Adjustment Frictions

This section uses Chile's experience during the 1998 sudden stop, triggered by Russia's default in August of that year, to document evidence of rising resource misallocation across firms, and the relevance of the adjustment frictions channel. I chose to focus on Chile's experience for two reasons. First, the shock the Chile's interest rate was exogenous. The country had few trade or financial ties to Russia, and prior to the crisis was experiencing a period of strong growth and sound macroeconomic fundamentals. Second, I have access to plant level data during this period, which allows me to directly show evidence of fluctuating productivity, misallocation and adjustment frictions.

3.3.1 Chile's Experience in the Aftermath of Russia's Default

Russia's default in 1998 precipitated a sharp increase in Chile's cost of external financing. The real interest rate rose by over 4.5 percentage points between 1997 and 1998. Higher borrowing costs caused the private sector to deleverage by reducing investment, which contributed to a sharp fall in output. Figure 3.1 shows the evolution of Chile's real interest rate between 1995 and 2007, along with deviations of detrended real GDP, investment and productivity from 1997 levels. The fall in all three measures in response to the sudden stop is large and persistent. Detrended output, investment and productivity remained below pre-crisis levels in 2007.

Figure 3.1: Economic Response during the Sudden Stop



Notes: Figures plot the deviation of the real interest rates (top-left), detrended real GDP (top-right), investment (bottom-left), and productivity (bottom-right) from pre-crisis (2007) levels. Real interest rate data are constructed using U.S. Treasury Bill rates and the JP Morgan's EMBI spread. Real GDP, investment and TFP series are obtained from the Penn World Tables. These series are detrended using an HP filter and are presented as deviations from detrended 1997 levels. The grey vertical line denotes the onset of the 1998 sudden stop.

The response of output and investment during sudden stop has been extensively studied, but fluctuations in aggregate productivity have yet to be fully explained. In the remainder of this section, I use establishment-level data covering the manufacturing sector in Chile between the years 1980 and 2007 to explore whether there is evidence of rising misallocation and adjustment frictions during the sudden stop. The data are collected annually by *Instituto Nacional de Estadisticas (INE)* through a survey of establishments employing ten workers or more. A detailed description of the data is available in appendix C.1.

3.3.2 Measuring Productivity and Misallocation

In this paper, I proposed that when interest rate are high and/or volatile the presence of capital and labor adjustment frictions contributes to falling productivity. In the presence of these frictions firms become less responsive to their productivity/demand shocks, which manifests itself as a rise in the dispersion of productivity and marginal products. In this section, I adopt the Hsieh and Klenow (2009) framework to assess whether the establishment-level evidence is consistent with this story.

3.3.2.1 Hsieh and Klenow framework

The underlying economic structure in Hsieh and Klenow (2009) is as follows: each industry s is composed of N_{st} intermediate goods producers operating a Cobb-Douglas production function; and total industry output is produced via a CES aggregator. As such, each firm i, in sector s, in year t faces an isoelastic demand for its output. In each period firms earn profits equal to production $((1 - \tau^y_{ist})\, p_{ist} y_{ist})$ net of labor and capital payments $(wl_{ist} + \left(1 + \tau^k_{ist}\right)(r_t + \delta)k_{ist})$. In each period, the firm chooses p_{ist} (price), l_{ist} (labor) and k_{ist} (capital) to maximize profits. Hsieh and Klenow (2009) interpret the terms $(1 - \tau^y_{ist})$ and $\left(1 + \tau^k_{ist}\right)$ as distortions. Subsequent work by Bartelsman et al. (2013) and Asker et al. (2014) show that frictions, including adjustment frictions and time to build also generate wedges between the marginal product of inputs and their marginal cost. I therefore consider the terms $(1-\tau_{ist}^{y})$ and $\left(1+\tau_{ist}^{k}\right)$ as reduced form measures that capture the presence of frictions.

The marginal product of labor ($MRPL$) and marginal product of capital ($MRPK$) derived from this framework are given by (3.1) and (3.2).[3]

$$MRPL_{ist}:\ (1-\alpha_s)\left(\frac{\varepsilon-1}{\varepsilon}\right)\left(\frac{p_{ist}y_{ist}}{l_{ist}}\right)=\frac{w}{1-\tau_{ist}^{y}} \tag{3.1}$$

$$MRPK_{ist}:\ \alpha_s\left(\frac{\varepsilon-1}{\varepsilon}\right)\left(\frac{p_{ist}y_{ist}}{k_{ist}}\right)=\frac{\left(1+\tau_{ist}^{k}\right)(r_t+\delta)}{1-\tau_{ist}^{y}} \tag{3.2}$$

where ε denotes the elasticity of substitution between varieties and is assumed to be equal to 4, as in Gopinath et al. (2017). Throughout this section I assume that $\alpha_s = \alpha = 1/3$. In appendix C.2 I show that the evolution of dispersion in $TFPR$ is insensitive to the use of a constant cost share by comparing the results reported here to those obtained using sector-specific U.S. cost shares, as is done in Hsieh and Klenow (2009), as well as to an alternative approach in which productivity is estimated using the Wooldridge (2009) extension of Levinsohn and Petrin (2003). The term $p_{ist}y_{ist}$ represents firm nominal value added, k_{ist} its capital stock and l_{ist} total employment adjusted for the number of days worked. Under this framework, plant-level $TFPR$ is proportional to the geometric average of marginal products. As a result, variation in $TFPR$ across firms only arises in the presence of frictions/distortions.

[3] The dispersion measures used throughout this section are those from Hsieh and Klenow (2009).

$$TFPR_{ist} = \frac{p_{ist}y_{ist}}{k_{ist}^{\alpha_s} l_{ist}^{1-\alpha_s}} \propto (MRPK_{ist})^{\alpha_s} (MRPL_{ist})^{1-\alpha_s} \propto \frac{\left(1+\tau_{ist}^{k}\right)^{\alpha_s}}{1-\tau_{ist}^{y}} \tag{3.3}$$

In the absence of frictions and/or distortions, the $MRPL$ of all firms is equal to the wage rate and $MRPK$ is equal to the cost of capital. Consequently, resources are allocated toward firms that are more productive and/or face higher demand and there is no dispersion across firms in either measure. The presence of frictions/distortions generates wedges between the return and cost of labor and capital; captured here by the terms $\left(\frac{1}{1-\tau_{is}^{y}}\right)$ and $\left(\frac{1+\tau_{is}^{k}}{1-\tau_{is}^{y}}\right)$. These wedges create dispersion in the marginal products of labor and capital, and are indicative of allocative inefficiencies.

To capture how the dispersion in marginal products and $TFPR$ evolves over time, I calculate the standard deviation of each measure across firms i in industry s in year t . Aggregate dispersion is the weighted average of dispersion in each industry s, where the weights are time-invariant and reflect the share of each industry's manufacturing value added over the whole period. More formally, for each measure X:

$$\mathrm{SD}\left(X_t\right) = \sum_{s=1}^{S} \omega_s \mathrm{SD}_s\left(X_{ist}\right) \tag{3.4}$$

where S is the total number of sectors in the economy, ω_s is the time-invariant industry weight, and $\mathrm{SD}_s\left(X_{ist}\right)$ is the standard deviation of X across all firms i, in sector s, in year t.

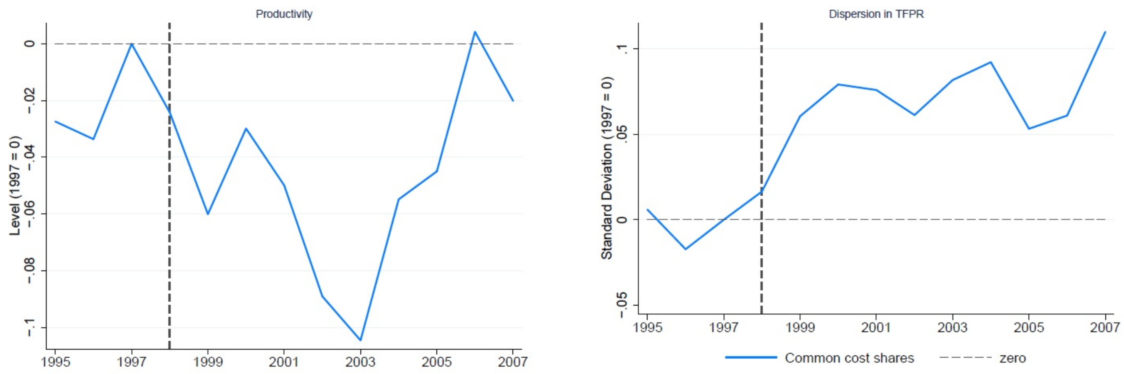
3.3.2.2 Productivity and Dispersion

Figure 3.2 shows that among this sample of firms productivity fell sharply during the sudden stop and did not return to pre-crisis levels until the late 2000s. I focus on a balanced sample of firms to facilitate a mapping between the data and the model I present in the next section, which abstracts from entry and exit. The evolution of productivity in the microdata is consistent with that observed in the aggregate data. The dispersion in the productivity ($TFPR$) rose by more than 9 percent between 1997 and 2004. The sharp increase in dispersion observed between 2005 and 2007 is outside the scope of my analysis and is likely driven by the commodity boom during this period.[4] Copper prices appear to play a lesser role in explaining dispersion dynamics prior to 2005. Between 1995 and 2005, the correlation between copper prices and dispersion in $TFPR$ is -0.17 , while it is -0.29 between the real interest rate and dispersion.[5]

[4]The commodity boom was driven by a sharp increase in copper prices in the mid-2000s. Between 2005 and 2006 the average copper price per pound rose from US$1.67 to US$3.05 (Chile, COCHILCO, Annuario 1987-2006).

[5]The correlation between copper prices and dispersion in $TFPR$ between 1980 and 2007 is 0.05. The correlation between copper prices and dispersion in $MRPK$ ($MRPL$) between 1995 and 2005 is 0.078 (-0.13), while the correlation between the real interest rate and dispersion in $MRPK$ ($MRPL$) is -0.44 (-0.21) during this same period.

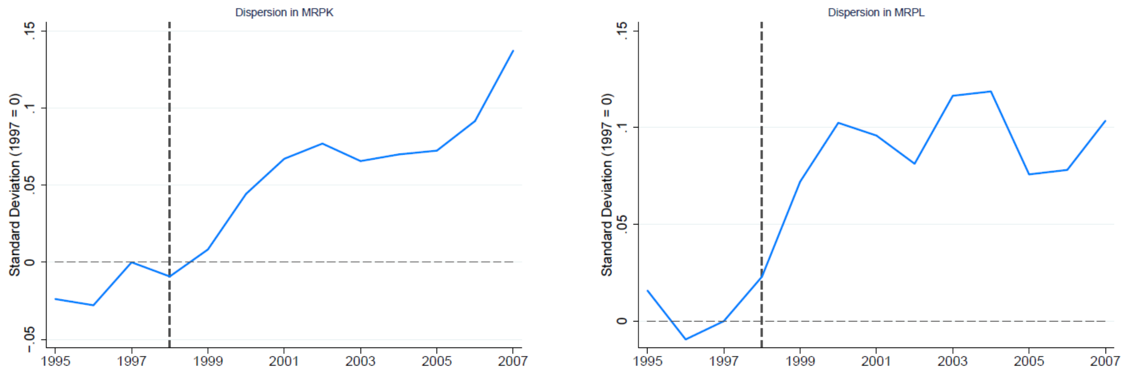
Figure 3.2: Productivity and Dispersion of $TFPR$ among Continuing Firms



Notes: Author's calculations based on ENIA manufacturing sector data. Both figures are presented for a balanced sample of firms that are present in the data between 1980 and 2007. The left figure plots the deviation of productivity from the pre-crisis (1997) level. The right figure plots the deviation of the dispersion of productivity from the pre-crisis (1997) level. Dispersion is calculated as the standard deviation across firms in a particular industry-year and aggregated using time-invariant employment shares. The grey vertical line denotes the onset of the 1998 sudden stop.

To get a better sense of what drives the rise in $TFPR$ dispersion, I consider the the weighted within-industry standard deviation of $MRPL$ and $MRPK$ between 1995 and 2007. Figure 3.3 suggests that the allocation of both factors was adversely affected by the crisis. Dispersion in $MRPK$ rose less than $MRPL$, but their evolution is similar; both experience a persistent rise in dispersion during the period of high interest rates. This rise in dispersion and concurrent fall in productivity is suggestive of deteriorating allocative efficiency. Since the dispersion in both marginal products rose, the evidence also points to the presence of distortions affecting both factors of production. In the next section, I explore whether there is evidence that adjustment costs associated with investment and labor may be playing a role.

Figure 3.3: Dispersion in Marginal Products



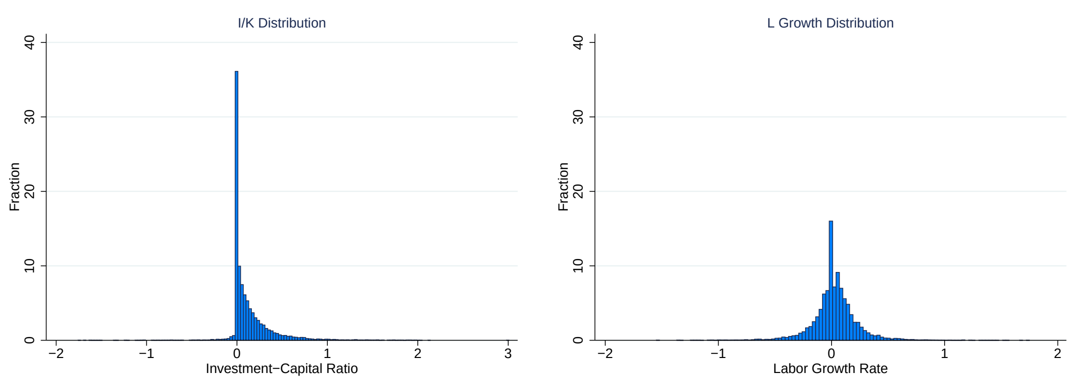
Notes: Manufacturing Census (ENIA) and author's calculations. Both figures are presented for a balanced sample of firms that are present in the data between 1980 and 2007. The left figure plots the deviation of the dispersion of $MRPK$ and the right figure plots the deviation of the dispersion of $MRPL$ from the pre-crisis (1997) level. For each variable, dispersion is calculated as the standard deviation across firms in a particular industry-year and aggregated using time-invariant employment shares. The grey vertical line denotes the onset of the 1998 sudden stop.

3.3.3 Adjustment Frictions

I emphasize the central role of adjustment frictions in contributing to fluctuations in productivity during sudden stop episodes. In particular, I propose that interest rate fluctuations interact with non-convex capital and labor adjustment costs by raising the fraction of firms that choose to delay investment and/or hiring during periods of high and volatile interest rates. As Cooper and Haltiwanger (2006) note, investment irreversibility may arise because secondary markets for capital goods are missing or weak. These types of markets tend to be less developed in emerging economies. Moreover, in Chile, labor regulations are cited as the top obstacle to doing business, according to the World Bank Enterprise Survey. Since these types of capital and labor adjustment frictions influence resource misallocation, they may be an important propagation mechanism of aggregate shocks on productivity. To ascertain whether these adjustment frictions are in fact empirically relevant in Chile, I follow Cooper and Haltiwanger (2006) in documenting plant-level evidence of non-convexities and irreversibilities associated with capital and labor adjustment.

I use investment rate and labor growth rate data for a balanced sample of firms between 1980 and 1997, which is the pre-crisis period I use to calibrate my model.[6] Moreover, focusing on this period shows that adjustment frictions are present even prior to the crisis. The investment rate distribution reported in figure (3.4) has a large mass around zero and is highly skewed to the right. The labor growth rate distribution also has a spike around zero, albeit far smaller than the one observed in investment rate distribution, and has a more symmetric distribution.

Figure 3.4: Distribution of $^{I}/_{K}$ and labor growth rate



Notes: Manufacturing Census (ENIA) and author's calculations. Both figures are presented for a balanced sample of firms that are present in the data between 1980 and 2007. The left figure is a histogram of the investment-capital ratio and the right figure is a histogram of the labor growth rate. The y-axis of both figures is the fraction of firms that fall into each histogram bin.

The summary statistics in table (3.1) illustrate a few key points. First, nearly

[6] Additional information on the construction of the investment rate and growth rate is available in the appendix C.1.

35% of (plant, year) observations report an investment rate less than 1% in absolute value and 11% report labor growth rate inaction. The high frequency of no investment in Chile contrasts to the far lower frequency in the United States (around 8%, reported by Cooper and Haltiwanger (2006)). These periods of inaction, particularly in the case of capital, are accompanied by high investment episodes, termed here as episodes in which investment or labor growth exceed 10% in the case of positive spikes and -10% in the case of negative spikes. Positive investment spikes account for nearly 40% of observations while positive labor growth rate spikes account for 30% of observations. In the case of investment and labor growth, negative spikes are less common. They occur in less than 2% of observations in investment and 19% in labor growth. The rarity of disinvestment is indicative of limited liquidity in capital resale markets, a feature that Chile likely shares with other emerging economies.

Table 3.1: Summary Statistics

Variable	**Investment Rate**	**Labor Growth Rate**
Average rate	13.3%	2.3%
Inaction rate	34.6%	11.1%
% Obs with negative value	3.1%	36.7%
Positive spike rate	39.1%	30.1%
Negative spike rate	1.4%	19.4%

Notes: Manufacturing Census (ENIA) and author's calculations. The summary statistics are presented for a balanced sample of firms that are present in the data between 1980 and 2007. The summary statistics are similar to those reported in Cooper and Haltiwanger (2006) as evidence of adjustment frictions in the capital and labor markets.

These summary statistics, along with the full investment rate and labor growth rate distributions are indicative of non-convex adjustment costs affecting labor and even more strongly, capital. The data on investment rates are consistent with a model featuring asymmetric non-convex adjustment costs, such as partial irreversibility. The data on labor growth rated are consistent with symmetric non-convex adjustment costs such as linear hiring/firing costs. I use several of the moments in this section (inaction rate, and positive and negative spike rate) to calibrate the industry equilibrium model described below.

3.4 Brief Theoretical Interlude

Throughout this paper I emphasize the interaction between changes in the level and volatility of the interest rate and adjustment frictions. The channel relies on a rise in the level or volatility of the interest rate leading more firms to delay investment/disinvestment and hiring/firing (i.e. an increase in inaction among firms). In this section, I review two results from the adjustment cost literature that demonstrate how changes in the interest rate affect the degree of investment inaction among firms.[7]

The Dixit (1995) framework can be used to show how a rise in the level of the interest rate generate an incentive to delay investment in the presence of fully (or partially) irreversible investment. Calcagnini and Saltari (2000) and Alvarez (2010) use a similar framework to show how interest rate volatility creates the same incentive. In both cases, a continuous time framework is used to derive closed form comparative statics. In this section I review the framework and present the

[7] In this section I focus on the investment margin, but the results would be similar for the hiring margin.

comparative static results, leaving the full re-derivation of results from Dixit (1995) and Calcagnini and Saltari (2000) to appendix C.3.

Consider the problem faced by a single firm. In one case, the firm faces transitory productivity/demand shocks and a constant interest rate. In the second case, it is characterized by permanent productivity and transitory interest rate fluctuations. The firm's productivity follows a geometric Brownian process.

$$dZ_i = \sigma_Z Z_t dW_t^z \tag{3.5}$$

Where dW_t^z is a Wiener process with zero mean and unit variance. The firm is risk neutral, as it is in the quantitative model, and therefore discounts future net revenue at the riskless interest rate r_t. When the interest rate is stochastic, it follows a Brownian process.

$$dr_t = \sigma_r r_t^{3/2} dW_t^r \tag{3.6}$$

The process (3.6) is convenient because it facilitates the derivation of analytical results. These results are consistent with those derived numerically by Alvarez and Koskela (2006) for a continuous time version of the $AR(1)$ process. The law of motion for capital is given by

$$dK_t = I_t d_t \tag{3.7}$$

which assumes zero depreciation. I assume that investment if fully irreversible and that the firm's reduced form profits are given by

$$\Pi_t = \frac{Z_t^\eta K_t^{1-\eta}}{1-\eta} \quad \eta < 1 \tag{3.8}$$

The firm maximizes its present discounted value of net profits

$$V\left(Z_t, K_t, r_t\right) = \max_{I_{it} \geq 0} E_t\left[\int_t^\infty e^{-\int_t^s r(u)du}\left(\Pi_t - I_t\right)\right] \tag{3.9}$$

This framework abstracts from the time-to-build assumption I include the the quantitative model. Here, investment becomes immediately productive and absent any adjustment costs $MRPK_t = r_t$.

Assume first that the the interest rate is constant ($r_t = r$). In this case, the firm's investment decision is fully characterized by a threshold $\bar{Z}_t$, which denotes the value Z_t below which the firm will choose to delay investment. This threshold is given by

$$\bar{Z}_{it} = \left[\frac{r}{K_{it}^{-\eta}}\left(1 - \frac{\eta}{s_n}\right)\right]^{1/\eta} \tag{3.10}$$

where s_n captures the real option value of delaying investment that arises from the presence of investment irreversibility and is given by

$$s_n = \frac{-\frac{\sigma_Z^2}{2} - \sqrt{\left(\frac{\sigma_Z^2}{2}\right)^2 + 2\sigma_Z^2 r}}{\sigma_Z^2} \tag{3.11}$$

It follows that

$$\frac{\partial \bar{Z}}{\partial r} = \frac{\left(\eta r \frac{\partial s_n}{\partial r} - \eta s_n + s_n^2\right)\left[\frac{r}{K_{it}^{\eta}}\left(1 - \frac{\eta}{s_n}\right)\right]^{1/\eta - 1}}{\eta K_{it}^{-\eta} s_n^2} > 0 \tag{3.12}$$

In (3.12) there are two effects at play. The interest rate affects the threshold directly through the user cost of capital (r) and indirectly through the option value. The direct effect pushes the inaction threshold higher because the incentive to invest falls with higher costs. The indirect effect is negative and pushes the threshold lower because when firms discount the future at a higher rate, the option value of waiting to take action falls. Here the direct effect dominates the indirect effect, which results in an expansion of the inaction region.

Now consider an alternative scenario in which firm-level productivity is constant and the interest rate is stochastic ($Z_t = Z$). In this case, the firm's investment decision is characterized by a threshold $\bar{r}$, given by

$$\bar{r} = Z^{\eta} K_t^{-\eta} \left(\frac{s_n + 1}{s_n \left(1 - \sigma_r^2\right)} \right) \tag{3.13}$$

where s_n again captures the real option value of delaying investment and is given by

$$s_n = {}^1\!/_2 - \sqrt{{}^1\!/_4 + {}^2\!/_{\sigma_r^2}} \tag{3.14}$$

A firm characterized by (Z_i, K_t) invests only if the interest rate is below $\bar{r}$. Interest rate volatility affects the threshold (3.13) directly through σ_r^2 and indirectly through s_n.

$$\frac{\partial \bar{r}}{\partial \sigma_r^2} = \frac{Z_i^{\eta} K_{it}^{-\eta}}{s_n^2 \left(1 - \sigma_r^2\right)^2} \left[\frac{-s_n^2 \left(s_n + 1\right)^2}{2 - 4 s_n} \right] < 0 \tag{3.15}$$

Equation (3.15) shows that as interest rate volatility rises, the threshold value of the interest rate at which firms are willing to invest falls (i.e. firms require a lower interest rate before they are willing to invest). One the one hand, when interest rate volatility rises firms want to invest more because the gains from low realizations of the interest rate will outweigh the losses from high realizations (direct effect). On the other hand, higher interest rate volatility raises the opportunity cost of investing, thus generating an incentive to delay investment (indirect effect). Since the indirect effect dominates in this case, a rise in interest rate volatility lowers $\bar{r}$.

From the point of view of a firm that is characterized by (Z_i, K_t) a single interest rate r prevails in the economy. When deciding whether or not to invest, each firm checks whether this r lies below or above $\bar{r}$. The result in the section shows that keeping the level of r constant and raising σ_r^2 will cause more firms to fall into the investment inaction region.

When the interest rate rise and/or interest rate volatility increases, more firms in the economy delay investment. In an economy with heterogeneous firms, this increase in the unwillingness of the firms to invest/disinvest will increase resource misallocation. These theoretical results also carry over to the case of labor adjustment frictions

3.5 Modeling the Effect of Interest Rate Shocks

I evaluate the effect of interest rate shocks using a model of risk neutral firms who face non-convex adjustment costs and are subject to transitory aggregate and idiosyncratic productivity/demand shocks and interest rate level and volatility shocks. Adjustment costs interact with the time varying interest rate level and volatility to generate time varying incentives to delay investment and hiring. Changes in the share of firms delaying investment and hiring contribute to fluctuations in output, dispersion of marginal products and aggregate productivity.

3.5.1 Production, Adjustment Costs and Stochastic Processes

The economy consists of a continuum of risk neutral firms facing a downward sloping demand curve with elasticity (η)

$$y_{jt} = B_t d_{jt} p_{jt}^{-\eta} \tag{3.16}$$

where B_t denotes the aggregate demand component, d_{jt} the idiosyncratic demand component and p_{jt} denotes prices. The resulting inverse demand curve is given by:

$$p_{jt} = (B_t d_{jt})^{1/\eta} y_{jt}^{-1/\eta} \tag{3.17}$$

Firms produce using a constant returns to scale technology:

$$y_{jt} = \tilde{A}_t \tilde{z}_{jt} k_{jt}^{\alpha} l_{jt}^{1-\alpha} \tag{3.18}$$

where $\tilde{A}_t$ denotes aggregate productivity, $\tilde{z}_{jt}$ idiosyncratic productivity, and k_{jt} is capital stock and l_{jt} is labor hours. Combining (3.17) and (3.18) obtains the firm's revenue function:

$$\tilde{y}_{jt} = p_{jt} y_{jt} = (B_t d_{jt})^{1/\eta} \left(\tilde{A}_t \tilde{z}_{jt} k_{jt}^{\alpha} l_{jt}^{1-\alpha}\right)^{1-1/\eta} \tag{3.19}$$

For tractability, I define $\kappa = \alpha\,(1 - 1/\eta)$, $\lambda = (1-\alpha)\,(1 - 1/\eta)$, $A_t = B_t^{1/\eta} \tilde{A}_t^{\,1-1/\eta}$ and $z_{jt} = d_{jt}^{1/\eta} \tilde{z}_{jt}^{1-1/\eta}$ and simplify $\tilde{y}_{jt}$:

$$\tilde{y}_{jt} = A_t z_{jt} k_{jt}^{\kappa} l_{jt}^{\lambda} \quad \kappa + \lambda < 1 \tag{3.20}$$

Under this formulation A_t combines aggregate productivity and demand, and z_{jt} combines idiosyncratic productivity and demand. I assume that the logarithm of A_t and z_{jt} follow an $AR(1)$ process.

$$\log(A_t) = \rho_A \log(A_{t-1}) + \sigma_A \varepsilon_{at} \quad \varepsilon_A \sim \mathcal{N}(0,1) \tag{3.21}$$

$$\log(z_{jt}) = \rho_z \log(z_{jt-1}) + \sigma_z \varepsilon_{zt} \quad \varepsilon_z \sim \mathcal{N}(0,1) \tag{3.22}$$

where ε_A is assumed to be i.i.d over time and ε_z is assumed to be i.i.d. across firms and time. In addition to stochastic aggregate productivity/demand (A_t), the economy also faces exogenous fluctuations in the level and volatility of the real interest rate. Real interest rate levels evolve according to the following $AR(1)$ process:

$$\log(R_t) = (1-\rho_R)\log\left(\bar{R}\right) + \rho_R \log(R_{t-1}) + \sigma_{Rt-1}\varepsilon_{Rt} \quad \varepsilon_R \sim \mathcal{N}(0,1) \tag{3.23}$$

where $\bar{R}$ captures the long run real interest rate. I allow the standard deviation of innovations to R_t (σ_R) to change over time according to an $AR(1)$ process:

$$\sigma_{Rt} = (1-\rho_\sigma)\bar{\sigma}_\sigma + \rho_\sigma \sigma_{Rt-1} + \sigma_\sigma \varepsilon_\sigma \quad \varepsilon_\sigma \sim \mathcal{N}(0,1) \tag{3.24}$$

where $\bar{\sigma}_\sigma$ denotes the long-run volatility. One assumption associated with (3.23) is worth noting. According to the timing assumption in (3.23), firms know one period in advance whether the distribution of shocks that determine the interest rate is changing in the next period. This is meant to capture the notion that firms understand the volatility of future financial conditions.

The firm enters each period (t) with a capital stock (k_{jt}), chosen in the previous period but not yet used in production, and labor hours (l_{jt-1}), chosen in the previous period and used in production in that period. If the firm chooses to purchase or sell capital and/or increase or decrease labor hours, it faces non-convex costs of adjustment. I adopt the adjustment cost structure of Bloom et al. (2018). A firm's capital stock evolves according to the standard law of motion

$$k_{jt+1} = (1 - \delta_k)\, k_{jt} + i_{jt} \tag{3.25}$$

where δ_k denotes the depreciation rate of capital and i_{jt} is current period investment. Capital adjustment costs $\left(AC_t^k\right)$ consist of partial irreversibility associated with disinvestment. This features captures the notion that firms can only sell capital at a fraction of the purchase price.

$$AC_{jt}^k = P_k |i_{jt}| \mathbb{I}\,(i_{jt} < 0) \quad P_k < 1 \tag{3.26}$$

Labor hours also evolve according to a law of motion

$$l_{jt} = (1 - \delta_l)\, l_{jt-1} + h_{jt} \tag{3.27}$$

where δ_l denotes the exogenous loss in hours worked arising from exogenous quits, retirement, sick leave, etc. The component h_{jt} captures the net change in hours worked, which could arise from hiring/firing workers or adjusting hours for existing workers. Labor adjustment costs $\left(AC_t^l\right)$ consist of linear variable costs denoted as a fraction of wages (wP_l), which arise from hiring, training and/or firing costs.[8]

$$AC^{l}_{jt} = wP_l|h_{jt}| \quad P_l < 1 \tag{3.28}$$

3.5.2 The Firm Problem

The continuum of risk-neutral firms described above exists in an infinite-horizon, discrete time, small open economy. $V(k_j, l_{j,-1}, z_j; A, R, \sigma_R)$ denotes the firm's value function. At any point in time, the firm is characterized by its capital stock, stock of labor hours, idiosyncratic productivity, aggregate productivity, the real interest rate and the current value of interest rate volatility. Firms choose investment (i_j) and adjustment of labor hours $\left(h_j\right)$ to maximize their present discounted value of revenue net of investment costs, wage bill and adjustment costs. Note that in the remainder of this section I drop the firm subscript (j).

Firms first choose whether or not to undertake any adjustment in capital or labor hours.

$$V(k, l_{-1}, z; A, R, \sigma_R) = \max_{i,h}(V^a, V^n) \tag{3.29}$$

In the case of no adjustment, both $i = 0$ and $h = 0$. Firms produce using k and $(1-\delta_l)\,l_{-1}$, pay the wage bill of labor hours used in production $(w(1-\delta_l)\,l_{-1})$ and carry depreciated capital $((1-\delta_k)\,k)$ and the stock of labor hours $((1-\delta_l)\,l_{-1})$ to the next period.

[8] A simple example is labor hours costs associated with new employee orientation.

$$V^n\left(k,l_{-1},z;A,R,\sigma_R\right)=\tilde{y}-w\left(1-\delta_l\right)l_{-1}+ \frac{1}{R}\mathbb{E}V\left(\left(1-\delta_k\right)k,\left(1-\delta_l\right)l_{-1},z';A',R',\sigma_R^{'}\right) \tag{3.30}$$

$$\text{st.:}\ \tilde{y}=Azk^{\kappa}\left(\left(1-\delta_l\right)l_{-1}\right)^{\lambda} \qquad \kappa+\lambda<1$$

In the case of any adjustment, either $i \neq 0$ and/or $h \neq 0$. Firms choose i and h at the beginning of the period, and subsequently produce using k and l, the latter of which incorporates any net change in labor hours (h). They also pay wages, investment cost (in the case of non-zero investment) and additional adjustment costs.

$$V^a\left(k,l_{-1},z;A,R,\sigma_R\right)=\max_{i,h}\left\{\tilde{y}-wl-i-AC^k-AC^n+\frac{1}{R}\mathbb{E}V\left(k',l,z';A',R',\sigma_R'\right)\right\} \tag{3.31}$$

$$\begin{aligned} \text{s.t: } \tilde{y} &= Azk^{\kappa}l^{\lambda} \quad \kappa+\lambda<1 \\ k' &= \left(1-\delta_k\right)k+i \\ l &= \left(1-\delta_l\right)l_{-1}+h \\ AC^k &= P_s|i|\mathbb{I}\left(i<0\right) \quad P_k<1 \\ AC^l &= wP_l|h| \quad P_l<1 \end{aligned}$$

Firms discount profits at the real interest rate (R). As a consequence, in this model interest rate shocks are equivalent to discount rate shocks. As I discussed in the previous section, and will discuss in more detail shortly, fluctuations in the interest rate interact with the adjustment costs firms face and affect their incentive to delay investment and/or hiring decisions. In particular, when interest rates are high and/or volatility, more firms will find it optimal to delay hiring and investment. Resource misallocation rises temporarily as inaction among firms grows and as a consequence, aggregate productivity falls.

3.5.3 Parametrization and Solution

The model is solved using value function iteration, the details of which are available in appendix C.4. The complete set of parameters I calibrate is:

$$\{\delta_k \delta_l, w, \kappa, \lambda, \rho_A, \sigma_A, \bar{R}, \rho_R, \sigma_R, \bar{\sigma}_\sigma, \rho_\sigma, \sigma_\sigma, P_k, P_l, \rho_z, \sigma_z\}$$

I divide these into three categories based on my parametrization strategy. One set of parameters is chosen using values found in the literature $\{\delta_k, \delta_l, w, \kappa, \lambda, \rho_A, \sigma_A\}$. The second set of parameters $\{\bar{R}, \rho_R, \sigma_R, \bar{\sigma}_\sigma, \rho_\sigma, \sigma_\sigma\}$, associated with the interest rate and volatility process, is chosen using real interest rate data for Chile. The last set of parameters $\{P, P_l, \rho_z, \sigma_z\}$, associated with the idiosyncratic productivity process and capital and labor adjustment costs, is chosen to be consistent with features of firm-level data.

I calibrate the model at a quarterly frequency.[9] Since the firm-level data are only available at an annual frequency, I aggregate observables obtained from an unconditional simulation of my model to compare model moments with data moments when setting the last set of parameters. The parameter values are reported in table (3.2).

[9]I do so because real interest rate data for Chile is only available between 1995 and 2015. I therefore need to use the quarterly data to calibrate the stochastic interest rate process.

Table 3.2: Parameter Values

δ_k	δ_l	κ	λ	w	ρ_A	$100\sigma_A$	$\bar{R}$	ρ_R	$100\sigma_R$	$100\bar{\sigma}_\sigma$	ρ_σ	$100\sigma_\sigma$	P_k	P_l	ρ_z	$100\sigma_z$
2.5%	8%	0.25	0.50	1	0.95	1.75	1.015	0.84	0.32	0.32	0.455	0.30	0.38	0.266	0.765	0.17

Notes: The parameter values are reported for the baseline model. The model is calibrated at a quarterly frequency.

3.5.3.1 Parameters from the literature

The depreciation rate of capital (δ_k) is set at 2.5%, or 10% annually. This value is a few percentage points higher than the 8% annually reported by Bergoeing et al. (2002), which is done for computational convenience.[10] I use the average annual turnover rate of 32% (or 8% quarterly) in Chile between 1995 and 2000 to calibrate (δ_l), based on Vergara (2005). I choose $\kappa = 0.25$, which corresponds to a capital cost share of $\alpha = 1/3$ and a 33% markup ($\eta = 4$).

I set wages (w) as the numaire. Setting wages as a parameter is justified in the small open economy literature by assuming that there is a perfectly competitive tradeable sector in the economy that operates a constant returns to scale technology using only labor as an input. Fixing real wages could be problematic if there is evidence that they fluctuate cyclically. This does not seem to be a concern in Chile during this period. According to Gambetti and Messina (2014), real wages in the manufacturing sector in Chile during the mid- to late-1990s were mostly acyclical.

Neumeyer and Perri (2005) set $\rho_A = 0.95$ and $\sigma_A = 0.0175$ in the version of

[10] Lower depreciation rates increase the number of grid points needed for computation. I ran the unconditional simulation using a 8% depreciation rate and the unconditional moments are not greatly affected.

their model with independent aggregate productivity and country risk shocks. I use this parametrization, despite the fact that their model is calibrated using data from Argentina, because no similar parameterization exists for Chile.[11]

3.5.3.2 Interest rate and volatility process

The real interest rate series for Chile, constructed using the J.P. Morgan EMBI spread and the U.S. T-Bill rate between 1998:Q1 and 2015:Q4, is used to calibrate $\{\bar{R}, \rho_R, \sigma_R, \bar{\sigma}_\sigma, \rho_\sigma, \sigma_\sigma\}$.[12] For this period, I have quarterly and daily data. The former informs $\{\bar{R}, \rho_R, \sigma_R\}$ while the latter informs $\{\bar{\sigma}_\sigma, \rho_\sigma, \sigma_\sigma\}$.

The average quarterly interest rate ($\bar{r}$) between 1998:Q1 and 2015:Q4 is 1.5%, which yields $\bar{R} = 1.015$. Estimating an $AR(1)$ process for the interest rate yields a persistence (ρ_R) of 0.84 and a standard deviation of innovations (σ_R) equal to 0.0032. To parametrize the interest rate volatility process I take advantage of daily real interest rate data. I generate the quarterly series of realized volatility as the within-quarter real interest rate range. A similar method is used in Alizadeh et al. (2002) in constructing a volatility estimator using stock trading data. The resulting series yields $\bar{\sigma}_\sigma = 0.0032$, and an $AR(1)$ estimation of the process yields a persistence (ρ_σ) of 0.455 and a standard deviation of innovations (σ_σ) equal to 0.0030.

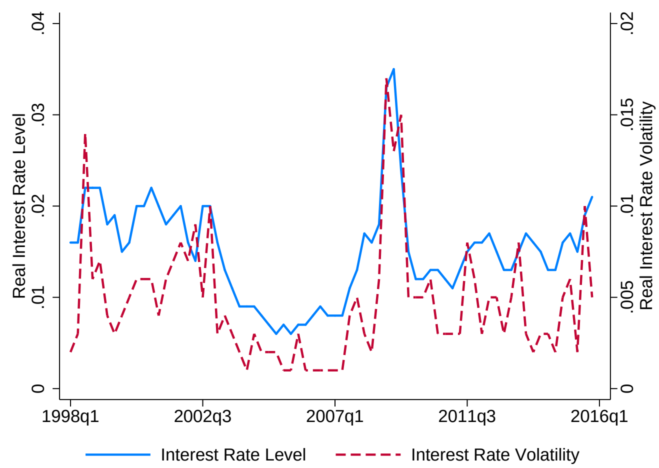
Figure 3.5 shows the evolution of the interest rate level and realized volatility series. It captures that the period 1998:Q3 through 2002:Q4 is characterized by high interest rates, and that the Great Recession triggered a less persistent increase in

[11] In the future I will calibrate these parameters to match moments of Chile's GDP growth rate series.

[12] Additional details on how the interest rate series is constructed are located in the appendix C.5.

interest rates. Interest rate volatility spikes in 1998:Q3, rises in for a few periods in 2002:Q2, as well as during the Great Recession. The correlation between the interest level and volatility series is positive and high (0.61). The model currently imposes zero correlation between these shocks in order to isolate the independent effect of interest rate level and volatility shocks on endogenous fluctuations in the dispersion of marginal products and productivity.[13]

Figure 3.5: Real Interest Rate Level and Volatility (1998:Q1-2015:Q4)



Notes: The real interest rate series for Chile is constructed using the JP Morgan EMBI speak and the US T-bill rate. The interest rate level is plotted in blue and the realized volatility series is plotted in dashed red. The realized volatility series is constructed using a similar method to Alizadeh et al. (2002).

3.5.3.3 Idiosyncratic productivity and adjustment costs

The remaining four parameters are chosen to be consistent with several moments from the micro-level data. I compute moments in the model by simulating a

[13] I leave it to future extensions to allow for correlated shocks that are more consistent with the data.

panel of 1,000 firms for 5,000 periods. Since each period corresponds to a quarter, I generate panel of annual data using the last 120 period (or 30 years). Output, investment and hiring are summed across four quarters, while labor is determined in the first quarter and capital in the last quarter. This timing is consistent with the idea that labor is used in production within the period (now a year) and capital is only used in production in the subsequent period. I then compare the moments generated by the model with moments constructed using firm-level data and a balanced sample of firms during the pre-crisis period (1980-1997).

The two adjustment costs parameters (P_l, P_k) are chosen to be consistent with key moments from the investment rate and labor growth rate distributions. In particular, I target the serial correlation, inaction rate, and positive and negative spike rates. In choosing ρ_z and σ_z, I first estimate the productivity process at the firm level using the regression:

$$\log\left(\hat{Z}_{ist}\right) = d_i + d_t + \rho^D \log\left(\hat{Z}_{ist-1}\right) + u^z_{ist} \tag{3.32}$$

where d_i denotes firm fixed effects, d_t denotes year fixed effects and $\hat{Z}_{ist}$ is given by:

$$\hat{Z}_{ist} = \frac{p_{ist} y_{ist}}{k_{ist}^{\kappa_s} l_{ist}^{\lambda_s}} \tag{3.33}$$

where $\hat{Z}_{ist}$ is calculated to be consistent with the corresponding object obtained in the model. As such, κ_s and λ_s are defined as $\kappa_s = \alpha_s (1 - 1/\eta)$, $\lambda_s = (1 - \alpha_s)(1 - 1/\eta)$, and $\alpha_s = \alpha = 1/3$, as in the empirical section above. I use ρ^D to calibrate ρ_z, and the time series average of the industry-weighted cross-sectional standard deviation of residuals u_{ist}^{z} $\left(\sigma^{D}\right)$ from regression 3.32 to calibrate σ_z. In appendix C.6 I consider two alternative ways of measuring 3.33 – using U.S. cost shares for α_s and using estimated elasticities (κ_s and λ_s) – in order to evaluate the sensitivity of ρ^D and σ^D to these approaches. The estimates of ρ^D and σ^D are similar across the three methods.

Table 3.3 summarizes the targeted moments and the corresponding model moments based on the parameters in table 3.2. The model does reasonably in capturing some of the regularities in the data. As Cooper and Haltiwanger (2006) note, the idiosyncratic shock process interacts in important ways with adjustment frictions. Spikes in investment and hiring are associated with the variability and persistence of these shocks. For instance, there is a tradeoff between matching the serial correlation of output and and the serial correlation of hiring. As the persistence of the idiosyncratic process rises, so does the serial correlation of hiring, which turns positive. As a result, my choice of ρ_z contributes to a negative serial correlation in hiring. Higher idiosyncratic volatility (σ_z) lower inaction and raises positive/negative spikes, particular for labor growth. The current parametrization imposes a high volatility, but is still only able to capture half of the very high idiosyncratic volatility observed in the data.

P_k is set to 0.4 and P_l is set to 0.38. The choice of P_k is in line with the estimates reported by Fuentes et al. (2006) for Chile. I do not have estimates to compare my choice of P_l, but it implies that hiring and firing costs equal 6.65% of annual wages. There is some evidence that hiring/firing costs are high in Chile, though this evidence cannot speak directly to whether the costs imposed here are accurate. Petrin and Sivadasan (2013) note that during the 1990s the maximum severance package, which is increasing in tenure, was raised from five to eleven months' wages. Further, the World Bank reports that the average severance pay, in salary weeks, for workers in Chile is 43.3. For comparison, the same figure in the United Kingdom is 4 weeks. Less information is available regarding hiring costs, but according to the World Bank Enterprise Survey around 58% of firms offer formal training in Chile, while only 45% of firms in the OECD do.

Given these parameters, the model captures the positive serial correlation in the investment rate and the negative serial correlation in the labor growth rate. It does well in generating inaction in labor growth, but produces very large positive spikes in labor growth, but does better in generating negative spikes. On the other hand, the model generates too much inaction in investment, which has been noted by Khan and Thomas (2008) and Fuentes et al. (2006) as a common feature of these models. The model does reasonably well in predicting positive spikes in investment, but does not generate any negative spikes.

For comparison, the last column of table 3.3 reports the statistics for an economy without adjustment costs ($P_k = P_l = 0$). The two economies differ particularly when it comes to investment. For instance, serial correlation of investment is negative in a model without adjustment costs. Unsurprisingly, the model with no adjustment costs is completely inconsistent with the lumpiness of firm-level investment. Overall, the results suggest that a model with adjustment costs is more consistent with the data than a model in which these costs are absent.

Table 3.3: Adjustment Costs: Micro and Model Moments

Variable	Data	Baseline	Frictionless
Persistence of $\hat{Z}_{ist}$	0.42	0.41	0.52
Standard Deviation of $\hat{Z}_{ist}$	0.40	0.21	0.19
Serial correlation (I)	0.14	0.07	-0.21
Serial correlation (H)	-0.16	-0.11	-0.22
Inaction rate (I)	34.6%	58.3%	0.14%
Inaction rate (H)	11.1%	10.9%	0.93%
Positive spike rate (I)	39.1%	32.5%	52.2%
Positive spike rate (H)	30.9%	66.5%	61.6%
Negative spike rate (I)	1.4%	0.0%	37.7%
Negative spike rate (H)	19.4%	10.3%	30.1%

Notes: The table reports the targeted moments (column 1) and corresponding model moments for the full model (column 2) and a frictionless model (column 3). The data moments are generated from the ENIA data using a balanced sample of firms that is present in the data between 1980 and 2007.

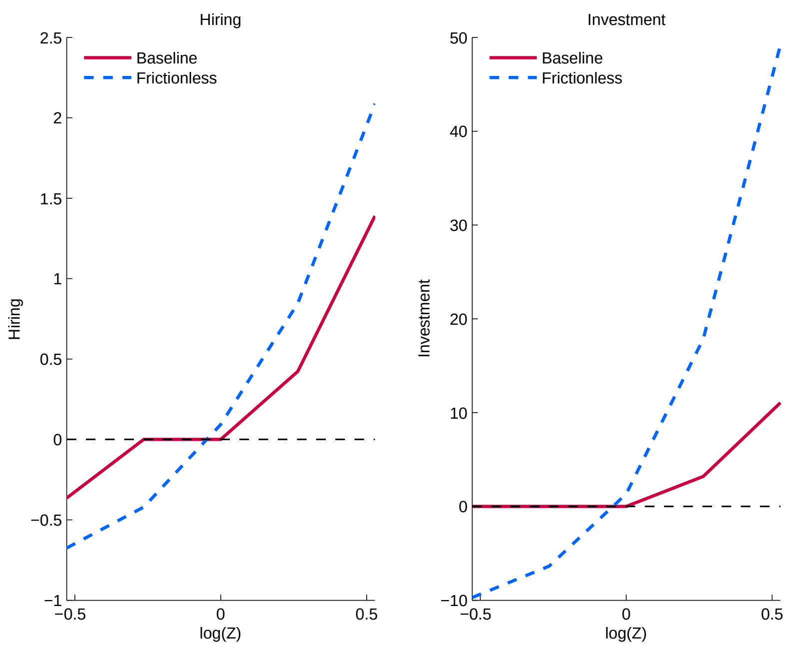
3.6 Responding to interest rate shocks

In this section I present the results of the model and the economy's response to an interest rate level and volatility shock.

3.6.1 Adjustment costs, interest rate and the firm's decision

Figure 3.6 shows how labor and capital adjustment frictions distort hiring and investment relative to a frictionless economy. In the absence of adjustment costs firms with that get low productivity draws lower labor hours and disinvest, while those with high draws expand. The discontinuity in the price of capital arising from partial irreversibility generates an incentive to delay investment. Similarly, linear labor adjustment frictions create an option value of waiting to hire/fire. Firms with low enough productivity will still find it optimal to scale down labor hours and those with sufficiently good conditions will want to hire. However, because hiring and firing is costly, some firms will find that the value of waiting for better (or worse) times is greater than the current returns to adjustment. The same intuition applies for investment. The right panel of figure (3.6) shows that $P_k = 0.38$ implies full irreversibility.[14] Firms will never find it optimal to disinvest, and when firms do invest, they do so at a rate below their counterparts in the frictionless economy.

Figure 3.6: Investment and Hiring: Baseline Model versus Frictionless Model

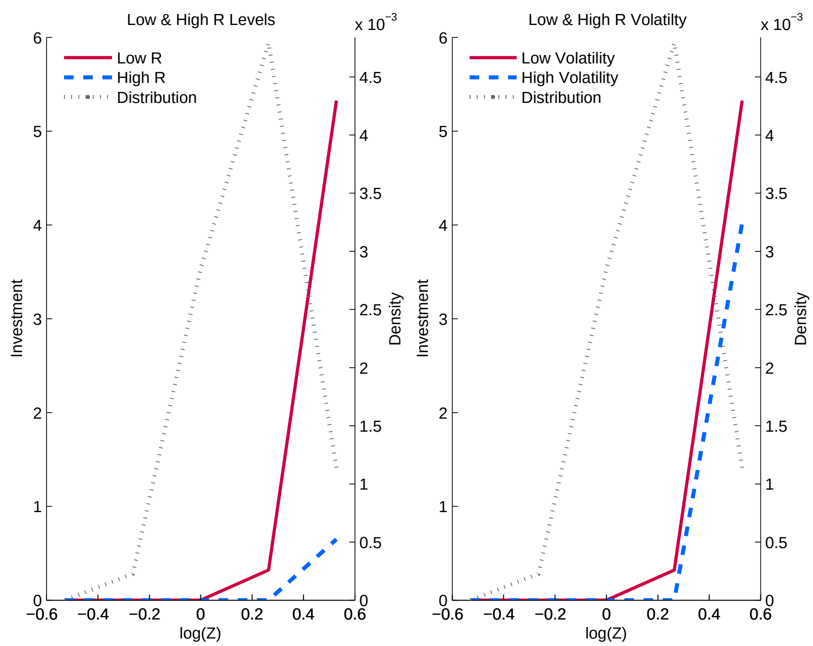


Notes: Hiring (left panel) and investment (right panel) decisions in the baseline model with adjustment frictions and a version of the model in which $P_k = P_l = 0$. Depicted are the decisions of when $A = 1.12$, $R = 1.02$ and interest rate volatility is low. The capital labor ratio is fixed ($^K/_L = 10$). The specific capital labor ratio is chosen because it represents nearly 1% of firm density in the ergodic steady state.

[14] Fuentes et al. (2006) find in their estimation that any sale price below 0.70 will imply complete irreversibility. Their results are comparable to my own since they too use manufacturing sector data from Chile.

As shown in section 3.4, these adjustment frictions interact with both the interest rate level and volatility. Focusing on the firm's investment decision, figure 3.7 compares the level of investment (solid and dashed line, left y-axis) when interest rates are low or high (left panel) and when volatility is low or high (right panel). The figure also includes the cross-sectional density of firms (dotted line, right y-axis). These are drawn for a particular capital-labor ratio that accounts for nearly 1% of firms in the stochastic steady state distribution.

Figure 3.7: Interest Rate and the Firm's Investment Decision



Notes: Both figures depict investment decisions for agents at a fixed capital labor ratio ($K/L = 10$) and fixed aggregate productivity at ergodic mean of 1. The chosen capital labor ratio represents nearly 1% of firm density in the ergodic steady state. In the left panel uncertainty is set to be low and $R^{low} = 1.012$ and $R^{high} = 1.028$. The aggregate state corresponding to R^{low} $\left(A = 1, R^{low} = 1.012, \sigma_R = \sigma^L\right)$ accounts for 25% of the states in the unconditional simulation of $5,000$ periods. The aggregate state corresponding to R^{high} accounts for 7% of the states in the simulation. In the right panel the interest rate is set to $R = 1.012$ and uncertainty is either low or high. The aggregate state corresponding to σ^L accounts for 25%of the states and that corresponding to σ^H accounts for 1% of states in the unconditional simulation.

Figure 3.7 indicates that the incentive to delay adjustment rises with the interest rate level and volatility. When interest rates are high and volatile, firms become less responsive to their productivity shocks. Only firms with the highest productivity still find it optimal to invest, albeit at a lower rate. For this capital-labor ratio, the reported distribution suggests that a rise in the interest rate level or volatility will induce a non-trivial fraction of firms to halt investment. Suppose instead the distribution was heavily concentrated at $\log(Z) \leq 0$, then the investment behavior of firms with this particular capital labor ratio would be unaffected. In short, the greater the fraction of firms concentrated around the inaction threshold as it expands, the greater will be the impact of changes in the level and volatility of the interest rate on investment behavior.

3.6.2 Economic Response to Interest Rate Shocks

I now consider the response of the model economy to an interest rate volatility and interest rate level shock. To produce the impulse responses I simulate two versions of $2,000$ economies for 100 periods. In each of these economies a shock hits the first version of the economy in the 45^{th} period, but does not hit the second. All idiosyncratic and aggregate shocks before and after this period are randomly drawn according to the stochastic processes described in section 5. The IRFs reported below are the cross-economy average percent difference between the shocked and unshocked simulations. More formally, the impulse response (x_t) of a series X at time t to a shock is given by

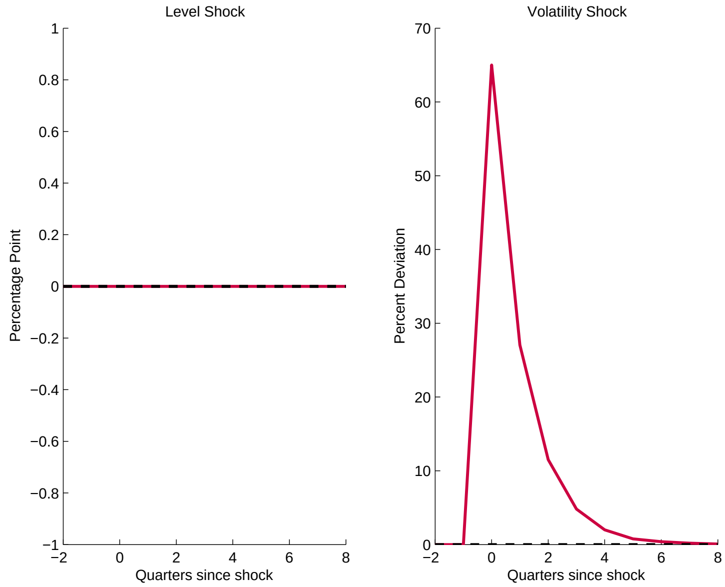
$$x_t = \frac{100}{N} \sum_{e=1}^{N} \log \left(\frac{X_{et}^S}{X_{et}^N} \right) \tag{3.34}$$

where e represents the economy, X^S represents the version of the economy that experiences the shock, and X^N represents the version of the economy that does not. The series I consider are output, investment rate, hiring rate, share of firms with zero investment, cross-sectional standard deviation of the marginal product of capital and labor and aggregate productivity. I calculate aggregate productivity as $\frac{Y}{K^{\kappa}L^{\lambda}}$ to be consistent with the series reported in figure 3.1, where Y, K and L represent aggregate output, capital stock and labor.

3.6.2.1 Interest Rate Volatility Shock

First consider the response to an interest rate volatility shock. Figure 3.8 shows the impulse that drives the results. Quarter zero represents the period in which the shock hits, and the vertical axis represents the average percent rise in volatility experienced across economies. The rise is lower than 100 percent because some of the economies already had high volatility when the shock hit. On average the shock increases volatility by 65% and begins to dissipate relatively quickly thereafter since it has low persistence. As the left panel shows, I am considering the response of the economy when the level of the interest rate is left unaffected by the volatility shock so as to capture the isolated effect of an increase in the interest rate volatility.

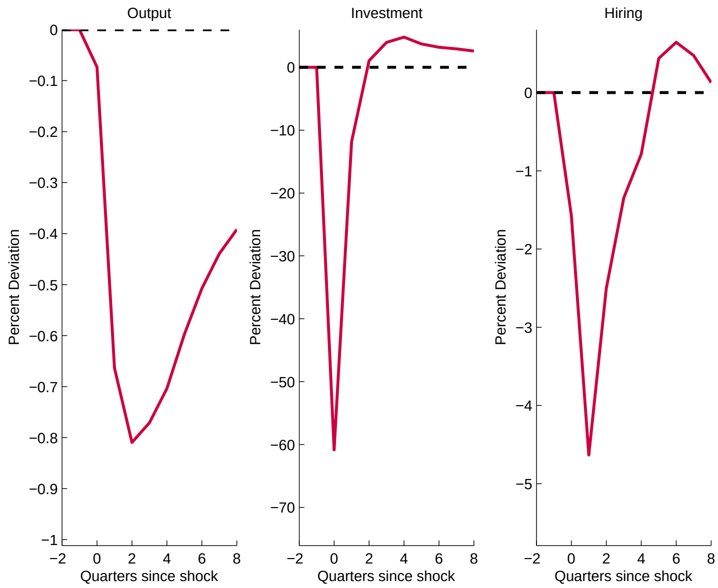
Figure 3.8: Impulse: Interest rate volatility shock



Notes: The figure shows the IRFs for the interest rate level (left) and interest rate volatility (right) shocks. In this simulation, only the interest rate volatility is shocked. To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

Figure 3.9 plots the response of aggregate output, investment and hiring. It shows a persistent fall in output that bottoms out in the second quarter after the shock and begins to recover thereafter. Investment plummets by over 60% on impact and rebounds within three quarters. The sharp fall in investment is in part a result of the partial equilibrium setting, as can be seen in Bloom et al. (2018). The effect of interest rate volatility on hiring is similar to investment, though weaker. Hiring falls by less than 5% and takes longer to rebound than investment. As seen in figure 3.7, an interest rate volatility shock expands the range of investment inaction and lowers investment demand. Both of these effects contribute to the initial fall in investment. As the shock dissipates the share of firms completely freezing investment falls. As these firms address their pent up demand for capital, investment rebounds and overshoots. The same dynamics explain the behavior of hiring.

Figure 3.9: Response to a Volatility Shock: Output, Investment and Hiring



Notes: The figure shows the IRFs in response to an interest rate volatility shock for output (left), investment (middle) and hiring (right). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

Consider now the effect of a volatility shock on productivity. Here I focus on the role of capital since it plays a larger role in driving the aggregate response of output. First, a rise in volatility triggers firms to freeze investment. This manifests itself as an increase in investment inaction, which rises by nearly 12 percent on impact; a similar rise in inaction is observed for hiring. This increase in the share of firms freezing investment activity is short-lived given the temporary nature of the shock. Since capital takes on period to become productive, the increase in investment inaction on impact will translate to a rise in the dispersion of marginal product of capital beginning one period after the shock, as can be seen in the second panel from the left in the figure below.

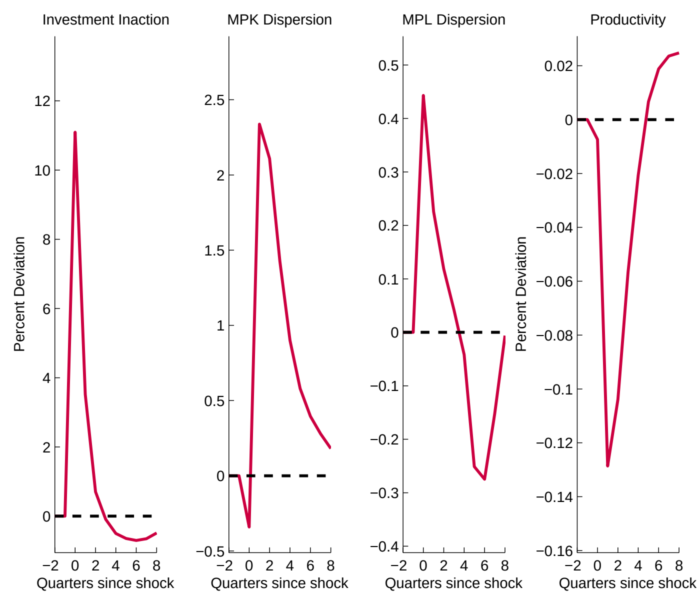
The initial fall in dispersion of MPK may seem puzzling at first, but it is driven by the fact that capital is predetermined when the shock hits while labor adjusts within the period. The time to build assumption on capital means that firms choose capital based on their expectations of future productivity, interest rate and labor. The fall in dispersion on impact is indicative of too much capital adjustment *ex ante*, given the pause in hiring in response to the shock *ex post*.[15] The third panel shows that dispersion in marginal product of labor rises when the shock hits and falls in subsequent periods. Since the rise in dispersion of MPL exceeds the fall in dispersion of MPK, productivity (seen in the last panel below) falls on impact.[16]

Productivity reaches its trough in the first period after the shock, which also coincides with the period in which dispersion in MPK reaches its peak. Note further that the overshoot in productivity beginning in the fifth period after the shock arises because as the shock dissipates firms begin to address their pent up demand for hiring and investment, as evidenced by the falling dispersion in marginal products. In fact, the overshoot in productivity coincides closely with the period in which dispersion in MPL falls sharply below zero.

[15] If I turn off labor adjustment frictions completely the initial fall in dispersion of MPK disappears. Additionally, if I assume that labor also faces a one period delay before becoming productive, the initial fall in MPK dispersion also disappears. The initial fall is therefore driven by the fact that labor faces adjustment frictions and that there is a difference in timing of capital and labor decisions.

[16] I have verified through various experiments that productivity will rise on impact if dispersion in MPK falls by more than the dispersion in MPL rises when the shock hits the economy.

Figure 3.10: Response to a Volatility Shock: I Inaction, Misallocation & Productivity



Notes: The figure shows the IRFs in response to an interest rate volatility shock for investment inaction (first from the left), MPK dispersion (second), MPL dispersion (third), and productivity (fourth). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

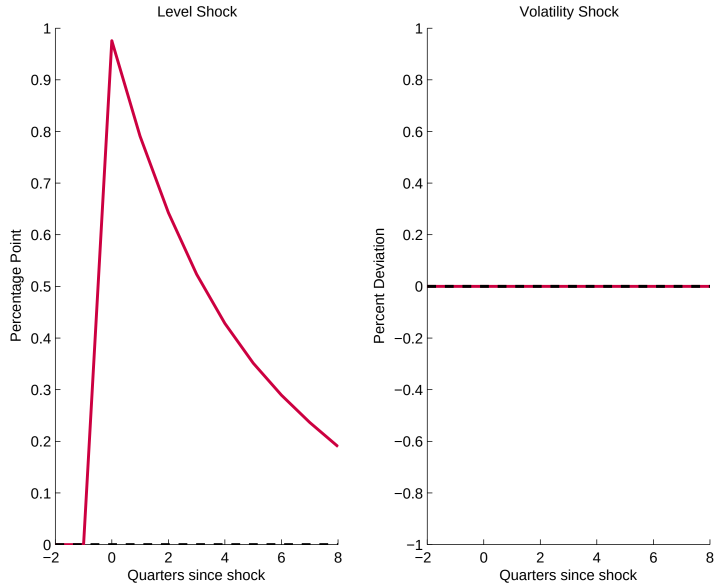
The response of the model economy is consistent with Chile's experience during the sudden stop. The volatility shocks triggers a freeze in investment, a rise in dispersion of marginal products and a fall in productivity. During the downturn the fall in output is far larger than he fall in productivity. While the response of the economy is qualitatively consistent with the response observed in the data, quantitatively the effect is small.

3.6.2.2 Interest Rate Level Shock

The response of the economy to an interest rate shock is quite similar to its response to a volatility shock. Figure 3.11 depicts the impulse, which increases the real interest rate by one percentage point. To put this into context, at the onset of the sudden stop Chile's real interest rate rose by 0.9 percentage points between the second and third quarters of 1998. The shock introduced in the model is therefore capturing the response of the economy to a shock of similar magnitude to that which hit Chile at the end of 1998. The one percentage point increase corresponds to around a 3 standard deviation shock to the interest rate level, which satisfies the definition of a sudden stop in Calvo and Talvi (2005).

The economy responds more strongly to the interest rate level shock than it does to the volatility shock. This reflects the fact that an increase in the interest rate creates stronger incentives to delay investment and hiring. The fall in output is more persistent and reaches its trough around one and a half years after the initial shock. This response is consistent Calvo et al. (2006) who find that across the 22 sudden stop episodes considered, average output falls by 7 percent within two years and recovers thereafter, albeit more quickly than in the model economy. The higher persistence in output, as well as other series, also reflect the the higher persistence of interest rate level shocks.

Figure 3.11: Impulse: Interest rate level shock

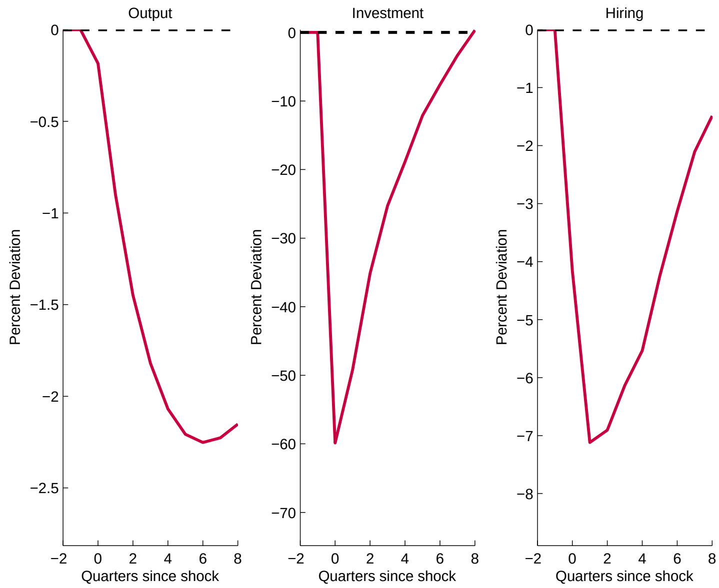


Notes: The figure shows the IRFs for the R level (left) and R volatility (right) shocks. In this simulation, only the interest level is shocked (a one percentage point increase). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

The figure also makes clear that investment and hiring fall slightly more than they do in response to an interest rate level shock, and recover at a slower rate. The same forces that drive an overshoot in investment and hiring following a volatility shock are present here, but simply take longer to take effect. Moreover, as is clear in the second panel in the figure below, the model again overpredicts the response of investment, which is due to a combination of strong investment frictions and the partial equilibrium setting.[17]

[17] For comparison, in the partial equilibrium exercise in Bloom et al. (2018), investment falls by 100 percent.

Figure 3.12: Response to a R Level Shock: Output, Investment and Hiring



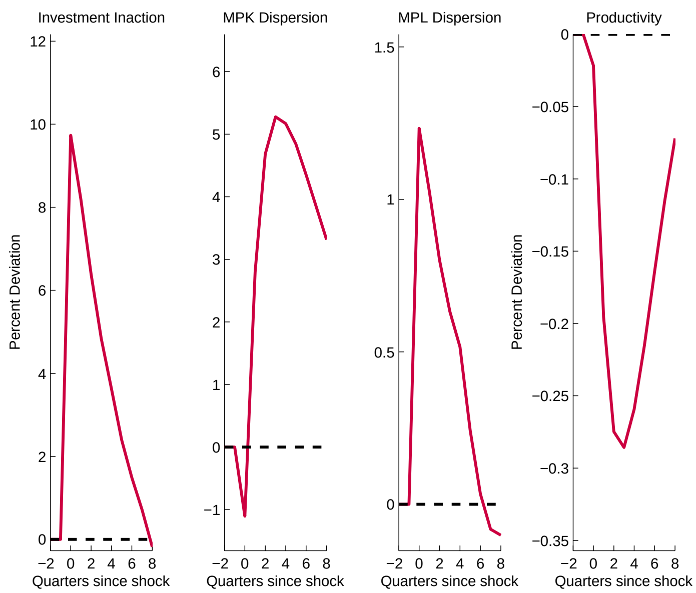
Notes: The figure shows the IRFs in response to an interest rate level shock (one percentage point) for output (left), investment (middle) and hiring (right). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

The effect of interest rate shocks on investment inaction, dispersion in marginal products and aggregate productivity are qualitatively the same and quantitatively stronger than the effect of a volatility shock. Namely, the shock leads to an immediate freeze in investment, which raises investment inaction on impact. This slowdown in in investment raises the dispersion in the marginal product of capital beginning one period after the shock. Since labor does not face the same kind of time-to-build friction, labor adjustment freezes and generates a rise in the dispersion of marginal product of labor in the same period that the interest rate rises. The fall in the dispersion in MPK in the period that shock hits arises from the difference in the timing associated with investment and hiring. Moreover, the fall in dispersion in

MPK is outweighed by the rise in dispersion of MPL, which leads to an initial fall in productivity.

Here again the fall in out is far larger than the fall in productivity, the later of which falls by only a small fraction (about one-thirteenth) of what is observed in the data. To put these effects into context, I consider a version of the model in which the interest rate is constant and aggregate productivity shocks drive the economy. Appendix C.7 reports the results of an alternative experiment in which I impose a 1.6 percentage point increase in the interest rate in order to generate the 4 percent decline in aggregate output observed in the data. Under this scenario productivity falls by 0.46%, or 1/9 of the decline observed in the data.

Figure 3.13: Response to a R Level Shock: I Inaction, Misallocation & Productivity

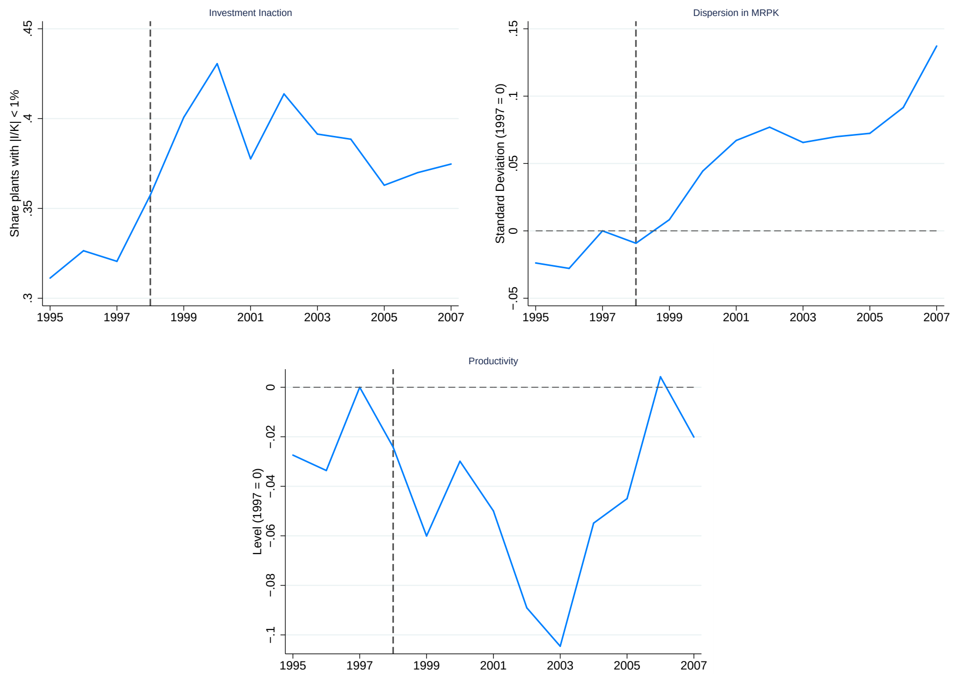


Notes: The figure shows the IRFs in response to an interest rate volatility level shock (one percentage point) for investment inaction (first from the left), MPK dispersion (second), MPL dispersion (third), and productivity (fourth). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

3.6.2.3 Comparison to the Data

The model predicts that aggregate productivity falls in response to a rise in the interest rate level or volatility because these shocks raise the value of waiting to invest/disinvest and adjust labor hours. As firms become less responsive to their own productivity shocks the dispersion in marginal products rises, signaling an increase in resource misallocation. Section 3.3 shows that during the 1998 sudden stop dispersion rose and productivity fell among firms in the manufacturing sector. Figure 3.14 complements these findings with evidence that during the same period, the share of firms delaying investment rose by around 8 percentage points between 1998 and 2000, which is consistent with the behavior of the model economy. Overall the model qualitatively captures important features of the firm-level data during the sudden, including the fall in output, investment, rise in resource misallocation and fall in productivity, but misses the mark quantitatively.

Figure 3.14: Investment Inaction, Disp. in MRPK and Prod. in the Data



Notes: Manufacturing Census (ENIA) and author's calculations. All figures are presented for a balanced sample of firms that are present in the data between 1980 and 2007. The top-left figure plots investment inaction, the top-right figure plots the dispersion of $MRPKR$, and the botton figure plots productivity. All figures are plotted ad the deviation from the pre-crisis (1997) level. The grey vertical line denotes the onset of the 1998 sudden stop.

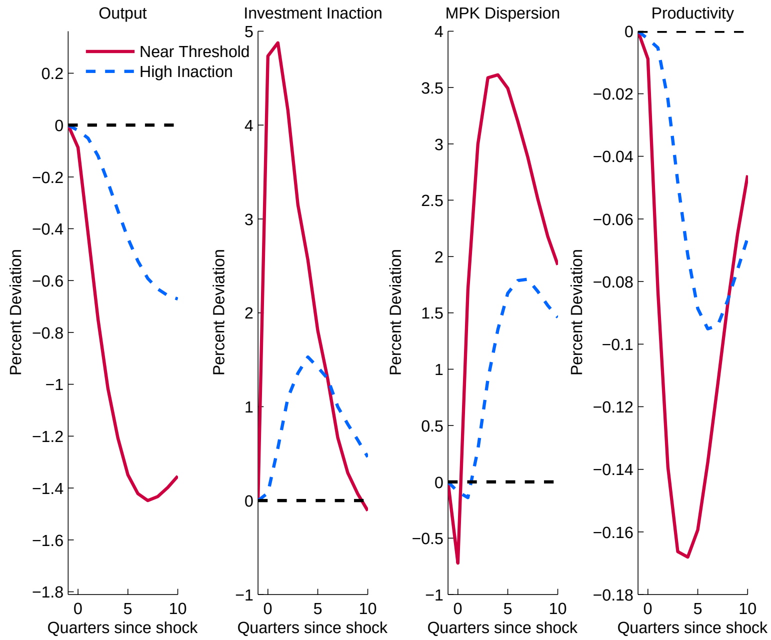
3.6.2.4 Exploiting Cross-Industry Variation

One prediction arising from the model is that interest rate shocks will generate larger fluctuations when many firms are at the investment and hiring thresholds than when many firms already find themselves in the inaction region. This arises from the fact that a rise in the interest rate level or volatility expands the inaction region. The more firms there are near this threshold when the shock hits, the more of them will respond by freezing investment and hiring, which triggers a rise in resource misallocation. On the other hand, if there are many firms already inside of the inaction region then they will simply continue to delay investment and hiring in response to the shock, which generates a weaker response.

Figure 3.15 demonstrates this prediction. For this exercise, I simulate the model response to a one percentage point interest rate level shock for two different initial conditions. The first simulation (depicted as the solid line in the figure below) has a large mass of firms near the investment and hiring thresholds. The second simulation (depicted as the dashed line) has a large mass of firms already inside of the inaction region. Output falls over twice as much and productivity falls nearly twice as much in the simulation with many firms at the threshold. Moreover, investment inaction and fluctuations in misallocation, measured as the rise in dispersion of MPK, are far stronger in the first simulation.

Currently, I identify the effect of interest rate fluctuations using only time variation in the data. Using the prediction of the model described here, in the future I can exploit differences across industries in the degree of investment hysterisis prior to the crisis to help me identify how adjustment frictions interacted with interest rate shocks to generate fluctuations in resource misallocation and productivity during the sudden stop.

Figure 3.15: Response to R Shock: the Effect of Distance from Threshold



Notes: The figures depict the IRFs of output (first to the left), investment inaction (second), MPK dispersion (third), and productivity (fourth) in response to a one percentage point shock to the level of the real interest rate. The economy represented with solid red line has a large mass of firms near the investment and hiring thresholds at the onset of the crisis. The economy represented with the dashed blue line has a large mass of firms already in the inaction region.

3.7 Conclusion

Given the close connection between output and productivity observed during sudden stops in emerging economies we need a better understanding of what drives the fall and recovery of productivity during these crises. Several channels, including entry and exit and capacity utilization have been explored in the literature. The former channel helps explain the long-run effects of sudden stops, while the latter emphasizes variation in measured productivity at the firm level. I focus on a complementary channel associated with short-run fluctuations in productivity and allocative efficiency within industries.

In particular, I ask whether resource misallocation arising from adjustment frictions contributes to fluctuations in aggregate productivity during sudden stops. As interest rates rise and the volatility of these rates increases firms freeze investment and hiring until interest rate conditions normalize. As a consequence firms become more unresponsive to their individual productivity and demand conditions, which in turn contributes to worsening allocative efficiency within industries. This rise in resource misallocation triggers a fall in aggregate productivity. Because spikes in the interest rate and volatility are temporary, the adjustment cost channel contributes to worsening misallocation in the short-run. After rates and volatility fall, firms begin to invest and adjust labor hours, which triggers a fall in resource misallocation and a rebound in productivity.

Using Chile's experience following Russia's default in 1998, I assess the relevance of the adjustment cost channel. Using manufacturing-sector firm-level data I show evidence of worsening allocative efficiency during the sudden stop. In particular, I show that declines in aggregate productivity coincide with a period in which the dispersion of marginal products was on the rise. Moreover, there is ample evidence that adjustment frictions are relevant given the high frequency of periods of no investment and hiring in the data.

To isolate the aggregate implications of interest rate fluctuations, I use a structural approach. I modify a standard heterogeneous firm investment model with with non-convex investment and labor adjustment costs and a stochastic interest rate that is subject to level and volatility shocks. The model is calibrated using the real interest rate and firm-level data from Chile. I find that in response to a rise in the interest rate level or volatility, firms freeze hiring and investment temporarily, which generate a rise in the dispersion of marginal products and a fall in aggregate productivity. The effect of these shocks is temporary and as conditions normalize firms begin to address their pent up investment and labor demand, which generates a strong rebound and mild overshoot.

While the model is qualitatively consistent with the evolution of output, investment, misallocation and productivity observed in the data during the crisis, it only explains a very small fraction of fluctuations during the sudden stop. The evidence suggests that adjustment frictions may contribute to aggregate fluctuations, but other channels play a role. In future research I plan to exploit industry-level variation to assess whether the model's prediction that industries with a large mass of firms near the investment and hiring thresholds are more affected by interest rate shocks than industries in which there is already little investment and hiring. Since the adjustment cost channel explains only a portion of the economy's response to interest rate shocks, I would like to incorporate additional channels to assess the relative importance of the adjustment costs emphasized here. In doing so I plan to incorporate firm heterogeneity and non-convex adjustment costs into a standard small-open economy general equilibrium model with an entry and exit margin to see whether adjustment frictions remain an relevant in propagating aggregate shocks.

A: Appendix for Chapter 1

A.1 Probabilistic Name and Address Matching Procedure

This paper combines ownership data obtained from BvD with firm-level data from the Business Register (BR) using EIN and probabilistic name and address matching. The LBD is derived from BR and information from both sources is used in the matching procedure. Both the BR and BvD data contain firm name, employer identification number (EIN), street address, city, state, zip code, and industry. While BR records generally have complete information on all variables, BvD records often have information on a subset of them.

BvD does not track EIN, name, and address information for entities over time. Instead, it provides a single record per entity. As a result, the matching is done for the entire period (2007-2013), rather than annually. As a first step, annual BR records dating back to 1976 are pooled to create a data set containing all unique EIN, firm name, and address records, along with identifiers indicating the years for which these records are valid. Similarly, the BvD firm name, address and EIN data are linked to the ownership data to identify the years in which entities are active. In the second step, the pooled BR and BvD data are cleaned to standardize firm name and address variables. Each standardized string variable (name, street address, and city) is then parsed to create a match code that will be used for probabilistic name and address matching.

The third step implements a ten-stage matching procedure, similar to McCue and Jarmin (2005). In the first stage, BvD records that contain EIN information are matched with BR records on this variable. In the second stage, all records that contain firm name and location information are matched based on fuzzed name, street address and city, and and exact 2-digit state code.[1] All remaining unmatched records are then matched in the third stage based on the fuzzed name and city and exact 2-digit state and 5-digit zip code. Remaining records are then iteratively matched based on different combinations of firm name and location information. Stages 4 through 6 use fuzzed entity name and different combinations of two location variables. Stages 7 through 9 use fuzzed entity name and different combinations of one location variable. In the tenth stage all records, including those matched in previous stages, are matched only on fuzzed name.[2]

As a consequence of probabilistic matching, a single BvD record can be linked to multiple BR records at the conclusion of the third step. The fourth step involves several stages aimed at disambiguating multiple matches. The first stage keeps matched records where the matched LBD firm and BvD entity are active in the

[1]The term fuzzed refers to matching on the match code for each variable generated in the second step.

[2]Note that all BvD records are considered for matching in stage 1 (EIN), stage 2 (name and full address), and stage 10. This is done because BvD does not report the dates for which the EIN and address variables are valid. A firm with multiple establishments may acquire new EINs and/or change the EIN used for reporting wages, or change the headquarter address over its lifetime. Reconsidering all firms for matching in stages 1, 2, and 10 is a flexible way of accounting for this reporting uncertainty, and various techniques are used in step 4 to identify the best (most accurate) match.

same years. Among remaining records, the second stage keeps those matched in the lowest stage (most strict criteria) in step three. The third stage creates a composite match quality score for each record based on firm name, city, state, and zip code (both 5-digit and 3-digit). The proximity of string variables (firm name and city) is determined using the Jaro-Winkler score. Records with the highest composite match quality score are kept. Among remaining multiple matches, those in which the LBD and BvD firms are active in the same industry are kept. The last stage drops records for which the best match has a sufficiently low composite score and records that could not be sufficiently disambiguated.

A.2 Two-Period Model

This section presents a two-period single-agent model of risky productivity-enhancing investment. This stylized model rationalizes the positive relationship between diversification and risky investment, and extends the model presented in section 1.5 by endogenizing the degree of diversification.

A.2.1 Setup

There are two periods, denoted by $t = 1, 2$ and the second period is composed of two sub-periods. Consider an owner who enters the first period ($t = 1$) with a_0 initial assets. The owner is assumed to be risk-averse with log utility. In the first period, the owner chooses how much to save (a_1) at an exogenous real interest rate (r), and how many firms (n) to operate. He pays $n\theta$ to operate these firms, where

θ is the entry cost per firm. These firms are not divisible and the owner holds 100% of the each firm's equity. It is assumed that firms become operational in the second period so that at the end of the first period, the owner consumes his remaining assets ($c_1 = a_0 - a_1 - n\theta$).

The owner enters the second period ($t = 2$) with savings chosen in the first period (a_1) and the n firms he controls. Each firm held by the owner produces via the following production function:

$$y = q^{(1-\alpha)} l^{\alpha} \tag{A.1}$$

where q is a measure of productivity and l is labor demand, which has a per unit cost of ω. In the second sub-period of $t = 2$, productivity (q) is known, labor (l) is chosen, and output is produced. Productivity (q) evolves according to the following process:

$$q = \begin{cases} (1+x) & \text{w/ prob. } \lambda \\ (1-x) & \text{w/ prob. } (1-\lambda) \end{cases} \tag{A.2}$$

where x is a choice variable reflecting risky investment and λ is a parameter denoting the probability of success. Investments are chosen in the first sub-period of $t = 2$, and are restricted to $x \,\epsilon\, [0, 1]$ to ensure positive output (y). First, the outcome of investment is uncorrelated across firms. Second, consistent with the notion of risky investment, higher investment is associated with higher potential returns, and a larger gap between productivity in the case of success versus failure. To highlight the role of diversification, it is assumed that there is no additional cost associated with implementing risky investment x.

Given each owner's initial assets (a_0), he chooses the number of firms to operate (n), savings (a_1), and the labor input (l_{2i}) and investment (x_{2i}) in each firm $i \epsilon [1, n]$ that he owns to maximize his expected utility.

$$\begin{aligned}
\mathbb{E}U &= \log(c_1) + \beta \mathbb{E} \log(c_2) \qquad \text{(A.3)} \\
\text{s.t.} \quad c_1 &= a_0 - a_1 - n\theta \\
c_2 &= (1+r)a_1 + \sum_{i=1}^{n} [q_{2i}^{(1-\alpha)} l_{2i}^{\alpha} - \omega l_{2i}] \\
q_{2i} &= \begin{cases} (1 + x_{2i}) & \text{w/ prob. } \lambda \\ (1 - x_{2i}) & \text{w/ prob. } (1-\lambda) \end{cases}
\end{aligned}$$

where β is the owner's discount factor, θ is the entry cost per firm, r is the exogenous real interest rate, α is the decreasing returns to scale parameter, ω is the per unit labor cost, and λ denotes the probability of success.

Two versions of this problem are solved. In the first version, the owner faces no additional constraint. As shown below, this results in owners borrowing in the first period to purchase the maximum number of firms, which enables them to diversify idiosyncratic risk in the second period. Under this first version, there is no heterogeneity in diversification. The second version imposes the following additional constraint:

$$a_1 \geq 0 \qquad \text{(A.4)}$$

Constraint (A.4) imposes that owners cannot borrow. This extreme assumption prevents owners from borrowing to open the maximum number of firms. It generates variation in the degree of diversification across owners. Admittedly, the assumption of no borrowing is quite extreme.

A.2.2 Solution

Across the two versions of the model, the underlying solution steps remain the same. The owner's problem is solved by starting in the second period ($t = 2$). Assuming that this period is split into two sub-periods separates the investment and labor decisions. In the second sub-period, a_1 is determined, q_{2i} is known and the owner chooses l_{2i} to maximize:

$$\max_{\{l_{2i}\}} \quad \ln\Big(\sum_{i=0}^{n} [q_{2i}^{1-\alpha} l_{2i}^{\alpha} - w l_{2i}] + (1+r) a_1 \Big) \tag{A.5}$$

For each l_{2i}, the solution yields:

$$l_{2i} = \left(\frac{\alpha}{\omega}\right)^{\frac{1}{1-\alpha}} q_{2i} \tag{A.6}$$

When x_{2i} is chosen in the first sub-period of $t = 2$, the owner's expected utility is:

$$\mathbb{E}U = \mathbb{E}\log\Big(\sum_{i=1}^{n} [\pi q_{2i}] + (1+r) a_1 \Big) \tag{A.7}$$

where $\pi = (1-\alpha)(\frac{\alpha}{\omega})^{\frac{\alpha}{1-\alpha}}$. Because π is common to all firms, the owner chooses $x_{2i} = x_2$ for the firms he controls. Using the fact that the probability of success follows a binomial distribution, define $\mathbb{P}(k, n, \lambda)$ as the probability of observing k successes in a binomial process with n trails and success probability λ:

$$\mathbb{P}(k, n, \lambda) = \begin{pmatrix} n \\ k \end{pmatrix} \lambda^k (1-\lambda)^{n-k} \tag{A.8}$$

In the first sub-period of $t = 2$, the owner chooses x_2 to solve:

$$V_2(a_1, n) = \max_{x_2} \sum_{k=0}^{n} \mathbb{P}(k, n, \lambda) \ln(\pi[k(1+x_2) + (n-k)(1-x_2)] + (1+r)a_1) \quad \text{(A.9)}$$

In the first period, the owner enters with initial assets (a_0) and no firms. He first chooses the number of firms (n) and then at the end of the period chooses savings (a_1) to solve:

$$V_1(a_0, 0) = \max_{a_1, n} \ln(a_0 - a_1 - n\theta) + \beta V_2(a_1, n) \quad \text{(A.10)}$$

A.2.3 Results

The two-period single-agent model described in the previous section cannot be solved analytically. The two versions of the model are solved numerically using the parameters listed in table A.1.

Table A.1: Parameters

Parameter	Value
α	0.75
ω	1.00
λ	0.55
θ	0.085
β	0.95
r	0.04
$\overline{n}$	10

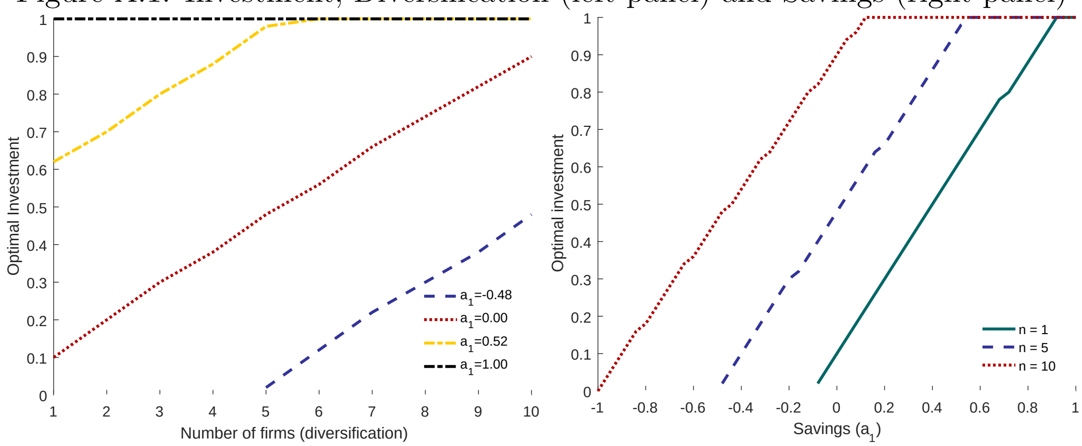
Notes: This table reports the parameter values used in the numerical solution of the model described in section A.2. α denotes the decreasing returns to scale parameter, ω denotes the per unit cost of labor, and λ denotes the probability that investment will be successful, θ is the per firm entry cost, β is the owner's discount factor, r is the real interest rate, and $\overline{n}$ is the maximum number of firms each owner can control.

In the table, α denotes the decreasing returns to scale parameter, ω denotes the per unit cost of labor, and λ denotes the probability that investment will be successful, θ is the per firm entry cost, β is the owner's discount factor, r is the real interest rate, and $\overline{n}$ is the maximum number of firms each owner can control.

A.2.3.1 Unconstrained

Starting off with the unconstrained model is useful to highlight the relationship between investment, diversification, and savings. Figure A.1 shows the owner's second period optimal investment (x_2) decision. Consistent with the empirical results and static model in section 1.5, the left panel of figure A.1 shows that across different levels of savings (a_1), optimal investment is increasing in diversification. This first result arises from owners finding safety in variety when firms are subject to idiosyncratic investment risk. The right panel of figure A.1 shows further that across different levels of diversification (n), optimal investment is increasing in savings. This second result shows that owners with higher savings are also able to use these savings to insure themselves against idiosyncratic risk.

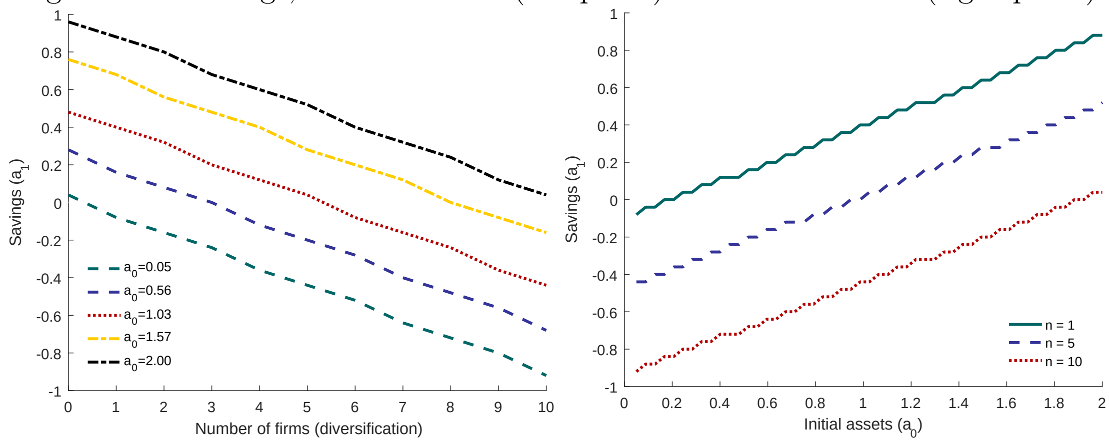
Figure A.1: Investment, Diversification (left panel) and Savings (right panel)



Notes: The figure in the left panel plots optimal investment (x_2) on the y-axis against diversification (n) on the x-axis, an each line represents a different level of savings (a_1). The figure in the right panel plots optimal investment (x_2) on the y-axis against savings (a_1) on the x-axis, an each line represents a different level of diversification (n). In this version of the model, the owner faces no additional constraints.

While the savings and diversification decisions are made simulataneously in the first period, it is useful to show how savings moves with initial assets and diversification separately. Figure A.2 shows the owners optimal savings (a_1) decision. For a given level of initial assets (a_0), savings are decreasing in diversification since opening more firms requires a higher start-up cost paid in the first period. For a given level of diversification (n), savings are increasing in initial assets. This arises because with higher initial assets, less borrowing is required to open the same number of firms.

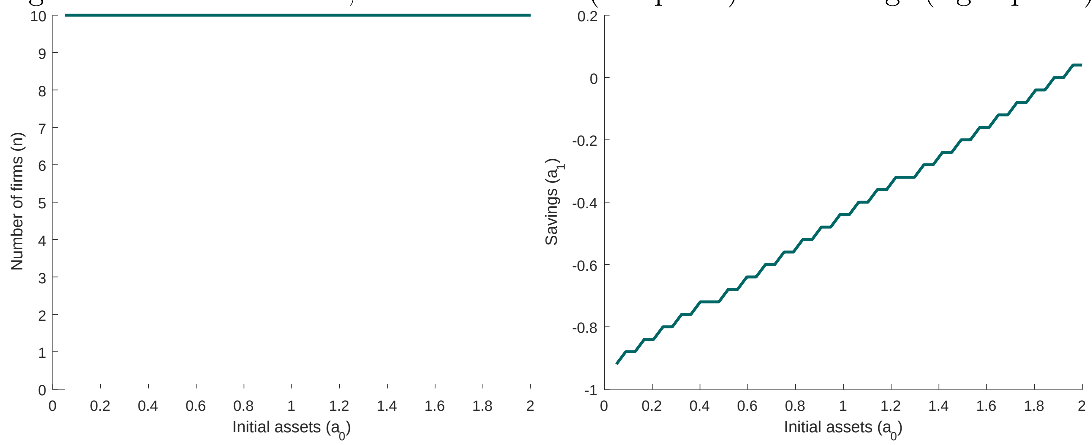
Figure A.2: Savings, Diversification (left panel) and Initial Assets (right panel)



Notes: The figure in the left panel plots optimal savings (a_1) on the y-axis against diversification (n) on the x-axis, an each line represents a different level of initial assets (a_0). The figure in the right panel plots optimal savings (a_1) on the y-axis against initial assets (a_0) on the x-axis, an each line represents a different level of diversification (n). In this version of the model, the owner faces no additional constraints.

Figure A.3 reports the owner's diversification (n) and savings (a_1) decisions as a function of initial assets (a_0), while figure A.4 reports the resulting second period risky investment (x_2) and expected value. Figure A.3 makes clear the implications of not imposing a borrowing constraint. Owners open the maximum number of firms (left panel) in order to diversify away the idiosyncratic risk arising from investment in the second period. Those with low initial assets borrow (right panel) in order to finance these firms. Only the wealthiest owners are able to finance the purchase of all firms out of their initial wealth and still save.

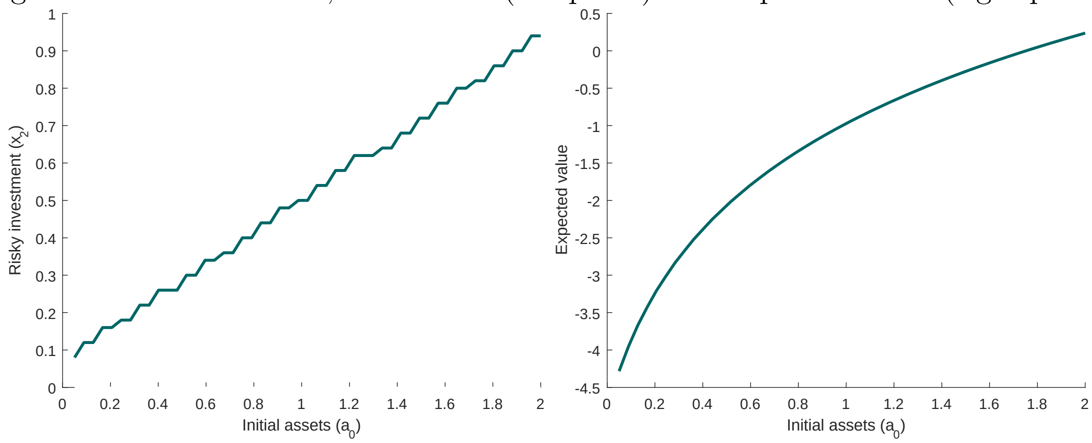
Figure A.3: Initial Assets, Diversificataion (left panel) and Savings (right panel)



Notes: The figure in the left panel plots savings (a_1) on the y-axis against initial assets (a_0) on the x-axis. The figure in the right panel plots the number of firms (n) on the y-axis against initial assets (a_0). In this version of the model, the owner faces no additional constraints.

The left panel of figure A.4 documents a positive relationship between initial assets and risky investment. This positive relationship is entirely driven by the positive relationship between savings and investment documented in the right panel of A.1. Intuitively, because higher initial assets are associated with higher investment and output, the right panel of figure A.4 shows that owner's expected value is also increasing in initial assets. The next section explores how imposing a borrowing constraint gives rise to differences in optimal diversification and generates a role for the risk-sharing channel observed in the data.

Figure A.4: Initial Assets, Investment (left panel) and Expected Value (right panel)



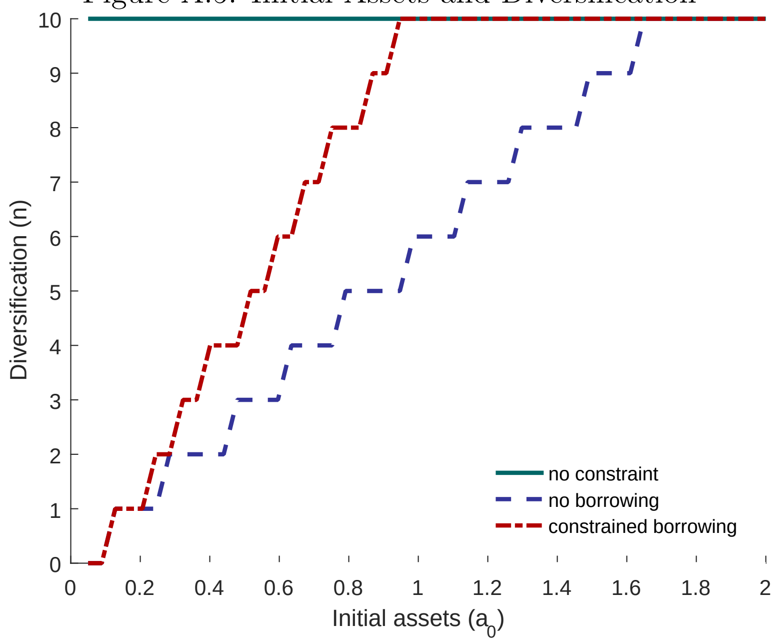
Notes: The figure in the left panel plots optimal investment (x_2) on the y-axis against initial assets (a_0) on the x-axis. The figure in the right panel plots the resulting expected value on the y-axis against initial assets (a_0) on the x-axis. In this version of the model, the owner faces no additional constraints.

A.2.3.2 Constrained

The two versions of the model with borrowing constraints hinder the owner's ability to open the maximum number of firms in the first period. Since this borrowing constraint affects the owner's first period decision, this section highlights differences in the owner's optimal diversification and savings decisions as a function of his initial assets in the first period and his subsequent investment decision.

Figure A.5 shows the relationship between initial assets and diversification for the three models. In the no constraint model (solid green line), regardless of initial assets owners choose the maximum number of firms. Under no borrowing (dashed blue line) or constrained borrowing (dotted red line) owners with higher initial assets choose a higher degree of diversification. Intuitively, while the no constraint model represents one extreme and results in the highest diversification, the no borrowing model represents another extreme and results in the lowest diversification. In the no borrowing model, only owners with initial assets above 1.8 are unconstrained and choose the maximum number of firms. In the constrained borrowing model, owners become unconstrained above initial assets of 0.8 and below this point can afford to open fewer than the maximum number of firms.

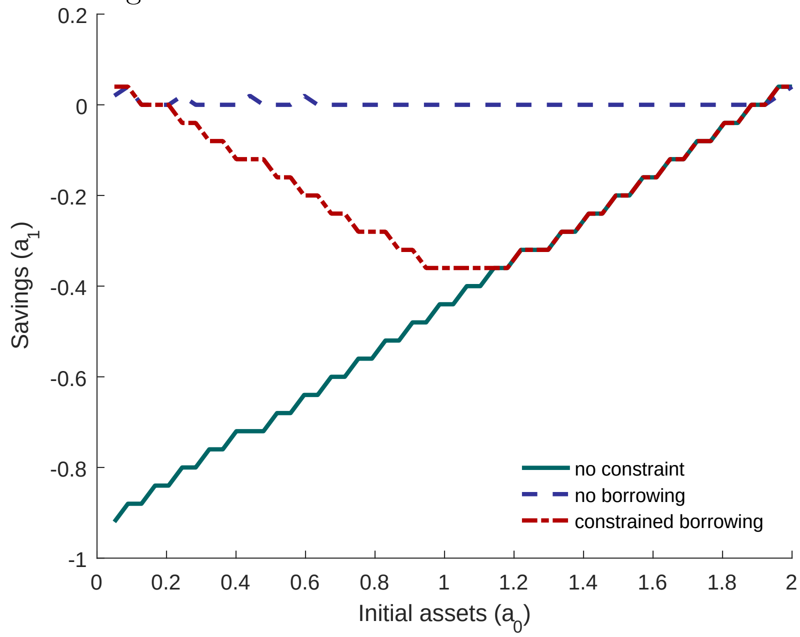
Figure A.5: Initial Assets and Diversification



Notes: The figure shows the optimal diversification (n, y-axis) policy as a function of initial assets (a_0, x-axis) for three versions of the model. The solid green line represents the no constraints model, the dashed blue line represents the no borrowing model, and the dotted red line represents the model in which the owner's borrowing is constrained to a fraction of his expected returns.

Figure A.6 plots the owner's savings decision as a function of his initial assets. In the unconstrained model owners withe lower initial assets borrow heavily to open the maximum number of firms. Only owners with the highest initial assets are able to open these firms and save. The constraints introduced in the no borrowing and constrained borrowing models force the owners to save more (borrow less) than they otherwise would. In the no borrowing model most owners choose neither to borrow nor save. Note the small increases in savings at $a_0 = 0.60$. When initial assets lie between 0.48 and 0.60 owners have sufficient assets to open three firms, but not to cover the fixed cost of opening a fourth firm. An owner with $a_0 = 0.60$ therefore saves the remaining initial assets. An owner with slightly higher initial assets of 0.64 can finance the purchase of a fourth firms, but due to the additional expense cannot save. This same logic explains other small spikes in the savings decision of owners in the no borrowing model. In the constrained borrowing model, the declining savings in the range of initial assets associated with constrained owners arises because as initial assets rise owners are opening more firms and as the left panel of figure A.2 shows, there is a negative relationship between savings and diversification. When initial assets surpass 0.8 owners become unconstrained, open the maximum number of firms, and make the same savings decisions as in the no constraint model.

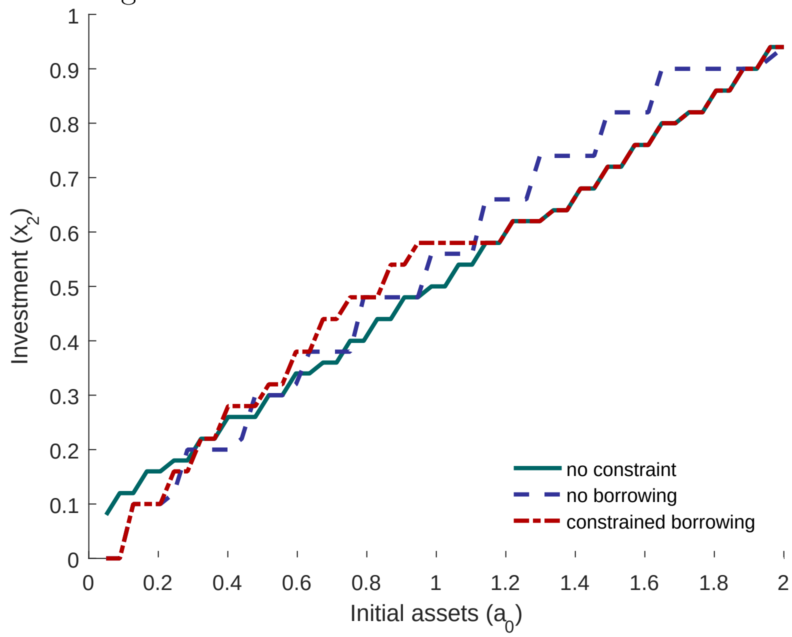
Figure A.6: Initial Assets and Diversification



Notes: The figure shows the optimal savings (a_1, y-axis) policy as a function of initial assets (a_0, x-axis) for three versions of the model. The solid green line represents the no constraints model, the dashed blue line represents the no borrowing model, and the dotted red line represents the model in which the owner's borrowing is constrained to a fraction of his expected returns.

Figure A.7 documents the optimal risky investment in each of the three models. In the no constraint model the positive relationship between initial assets and investment arises because savings is increasing in initial assets and investment is increasing in savings. Diversification plays no role since all owners hold the maximum number of firms in this model. In the no borrowing model, the positive relationship between initial assets and investment is driven almost entirely by the positive relationship between investment and diversification since regardless of the level of initial assets savings is very close to zero. In the constrained borrowing model, the positive relationship between investment and initial assets is driven both by diversification when initial assets are below 1 and owners hold fewer than the maximum number of firms and by savings when initial assets are above 1 and owners hold the maximum number of firms.

Figure A.7: Initial Assets and Diversification



Notes: The figure shows the optimal investment (x_2, y-axis) policy as a function of initial assets (a_0, x-axis) for three versions of the model. The solid green line represents the no constraints model, the dashed blue line represents the no borrowing model, and the dotted red line represents the model in which the owner's borrowing is constrained to a fraction of his expected returns.

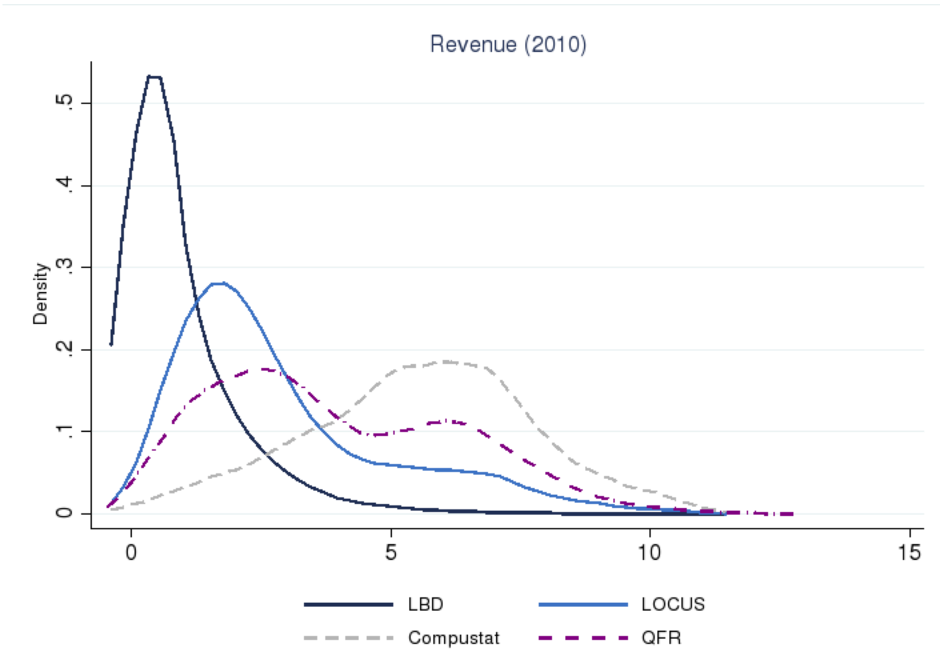
B: Appendix for Chapter 2

B.1 Comparison of LOCUS and QFR data

Although QFR surveys both small and large firms in the manufacturing sector, LOCUS has better coverage of small firms. To be consistent with figures 2.3 and 2.4, we focus on the year 2010. Since coverage in the QFR is greatest in the manufacturing sector, we also focus on this sector in the LBD, Compustat, and LOCUS. In the figure B.1, we plot the distribution of real revenue, which is available for all four data sources. The three non-LBD data sources have a greater mass of large firms than the LBD. While QFR contains smaller firms than Compustat, the LOCUS distribution of real revenue is closer that of the LBD than QFR.

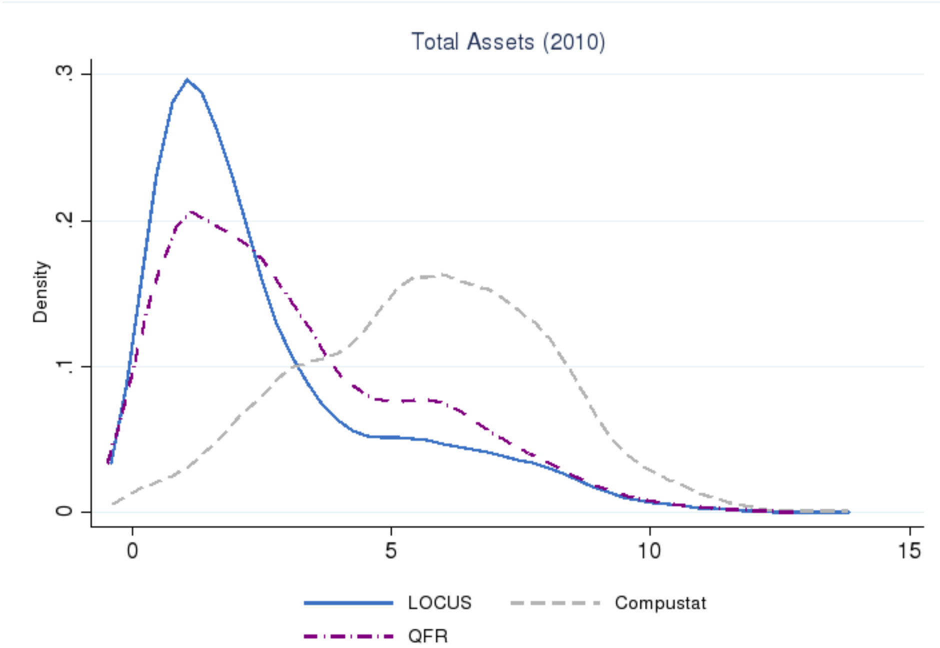
In figure B.2, we plot the distribution of log real total assets for the three data sources where this variable is available – Compustat, LOCUS and QFR. Again, we see that while QFR's coverage of small firms is better than Compustat, it is worse than LOCUS. Moreover, LOCUS contains data on both small and large firms in sectors outside of manufacturing, while QFR surveys only large firms outside of manufacturing.

Figure B.1: Comparison of Revenue Distributions (2010, Manufacturing Sector)



Notes: This figure compares the distribution of firm-level revenue in the manufacturing sector across four samples in 2010. The first sample contains firms in the LBD, the second contains LOCUS (both private and public firms), the third contains Compustat firms (public firms), and the last are firms in the Quarterly Financial Report (QFR). The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements.

Figure B.2: Comparison of Total Assets Distributions (2010, Manufacturing Sector)



Notes: This figure compares the distribution of firm-level total assets in the manufacturing sector across three samples in 2010. The first sample contains firms in LOCUS (both private and public firms), the second contains only Compustat firms (public firms), and the last contains firms in the Quarterly Financial Report (QFR). The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements.

B.2 Matching Procedure

Orbis and Compustat contain entity name, employer identification number (EIN), city, state and zip code; Compustat additionally contains street address information. LBD records can be linked to the business register, which contains firm name, EIN, street address, city, state and zip code. The LBD/SSEL is linked to Orbis and Compustat separately and annually using a multi-stage probabilistic matching procedure similar to that used in McCue (2003) to construct the Compustat-

SSEL bridge that is available through 2005.

In all, there are nine stages to our matching procedure. In the first stage, Orbis and Compustat records that have EIN information are matched to the LBD/SSEL based on this variable. All remaining unmatched records, along with those that do not contain EIN but contain location information, are then matched based on fuzzed entity name, address, city, and exact state and zip code.[1] For Compustat the second stage matches records based on fuzzed name street address, city and exact state. This second stage cannot be implemented for Orbis because street address is unavailable. The third stage matches records based on fuzzed name and city, and exact state and zip code. Stages 4 through 6 rely on different combinations of fuzzed entity name and two location identifiers. Finally, stages 7 through 9 use fuzzed entity name and one location identifier. In contrast to McCue (2003), we do not base any matches solely on fuzzed entity name.

Due to the probabilistic nature of the matching, one Orbis/Compustat record will initially be linked to multiple records in the LBD/SSEL. First, we clean the annual matched data. Each potential match is evaluated based on the similarity in location (zip code, city and state), name, and industry code between the Orbis/Compustat record and its match in the LBD/SSEL. We rely on the Jaro-Winkler distance to measure the similarity between each matched name and city.[2] For each Orbis or Compustat record, only the highest quality match is retained. This first stage of cleaning results in a data set in which each record, corresponding

[1]The term fuzzed refers to our use of the DQMATCH procedure implemented in SAS.

[2]We thank Mark Kutzbach at the U.S. Census Bureau for giving us access to the Jaro-Winkler comparator code.

to a firm-year observation, in Orbis/Compustat is matched to just one record in LBD/SSEL.

We further clean our matches to obtain a panel cross-walk between Orbis/Compustat entities and firms in the LBD/SSEL by taking advantage of the information on matches over time. First, if an Orbis/Compustat entity consistently matches with only one LBD/SSEL firm, but a match was not achieved for all the years for which we have records, the LBD/SSEL firm identifier is imputed. Second, if an Orbis/Compustat entity matched to multiple firms over time, we keep the firm(s) that were matched with the strictest criteria. Third, if an Orbis/Compustat entity still matches to multiple firms over time based on the same criteria, we keep the firm(s) with the highest overall match score. One additional imputation is done for Compustat. A key difference between Orbis and Compustat is that the entity name and location variables in Compustat are static over time and represent information provided by the entity in its latest filing. As a result, for Compustat firms if multiple firm matches remain after the previous steps have been implemented, we take the latest match and impute it backwards.

As a final check, we bring in firm employment and age information from the LBD. For records in which we imputed the LBD/SSEL firm due to multiple firm matches over time, we only consider the imputation valid if we observe firm employment or age in the year the imputation was made. We revert to the original firm match if the imputation is considered invalid. After this step is implemented we still have cases where one Orbis/Compustat entity is matched to multiple firms over time. This could be picking up firm-level reorganization and/or mergers and acquisitions. In order to ensure that multiple matches are not driven by the probabilistic nature of our matching, we drop cases where an Orbis/Compustat entity matched with more than three LBD firms. Very few observations are dropped by this criteria, and our implicit assumption is that in the 11 years used in our matching we don't expect a firm to go through more than three reorganizations. Finally, we drop cases where a firm matches with more than two entities and the matches are based on fuzzed name and less than three location criteria.

After these steps have been implemented, we end up with two data sets. Our Orbis-LBD/SSEL data which contains nearly 78 percent of underlying Orbis entity-year observations, corresponding to 70 percent of entities in the underlying Orbis data. 76 percent of these matches are based on EIN, while an additional 18 percent are based on name, zip code, city and state. Our Compustat-LBD/SSEL data contains 84 percent of underlying Compustat entity-year observations, corresponding to 79 percent of entities in the underlying Compustat data. The match rate at the firm-level is consistent with the match rate of Compustat firms reported in McCue (2003) once we take into account that none of our matches are made solely on fuzzed name. 75 percent of these matches are based on EIN, while an additional 6 percent are based on name and full address information.

As a final step in constructing LOCUS, we combine Orbis-LBD/SSEL and Compustat-LBD/SSEL matched datasets to ensure that we do not double count any publicly-listed firms that are in both data sets. We begin by matching the two data sets. If a firm appears in both matched data sets, we give preference to the the data source (Orbis or Compustat) with the longest sample period. Since all

Compustat financial statements are consolidated, we expect that only one Compustat entity matches to a LBD firm in each year. In a very limited number of cases more than one Compustat entity matches to one LBD firm in a year, and in all of these cases the match is based either on EIN or fuzzed name and three location variables. Because these matches are of high quality, they most likely represent a reorganization. A visual inspection of the balance sheet in these cases leads us to favor summing financial variables across the Compustat entities in the year we observe the reorganization. Orbis entities file unconsolidated financial statements. As a result, we expect that several Orbis entities may match to a single LBD firm in one year. Since we are interested in tracking firm performance over time, we may be concerned about changes in the composition of Orbis entities reporting balance sheets for the same firm over time. To address this concern, we only keep the set of Orbis entities associated with a particular firm that consistently report their balance sheets. The sample from which we draw on for our regression analysis consists of nearly 198,000 unique firms, 97 percent of which are privately held.

B.3 Conditional Nonlinear Relationships During the GR

The figures in this section are generated by regressing short-term leverage on size, size squared, age, collateral, profitability, labor productivity and industry fixed effects separately for private and listed firms in 2006 and 2009.

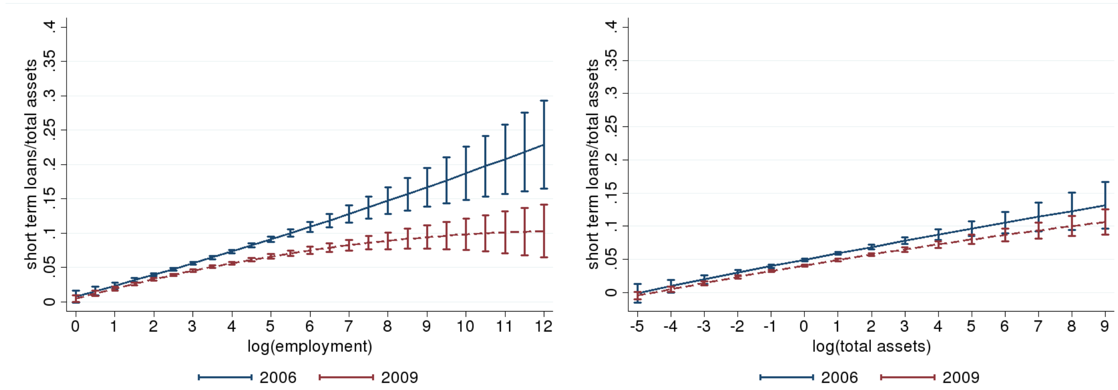
$$\begin{aligned} STLEV_i = &\alpha + \omega_s + \beta_1 \log(SIZE_i) + \beta_2 \log(SIZE_i)^2 + \beta_3 AGE_i + \\ &\beta_4 COLLAT_i + \beta_5 PROFIT_i + \beta_6 PROD_i + \epsilon_i \end{aligned} \tag{B.1}$$

where $STLEV_i$ is short-term debt over total assets, ω_s captures industry fixed effects, $SIZE_i$ is measured by either employment or total assets, AGE_i is firm age, $COLLAT_i$ is total fixed assets over total assets, $PROFIT_i$ is net income over total assets, and $PROD_i$ is total employment over revenue.

The results for private firms are reported in figure B.3 and for listed firms in figure B.4. In both figures, the left panel uses log employment as the measure of size and the right panel uses log total assets.

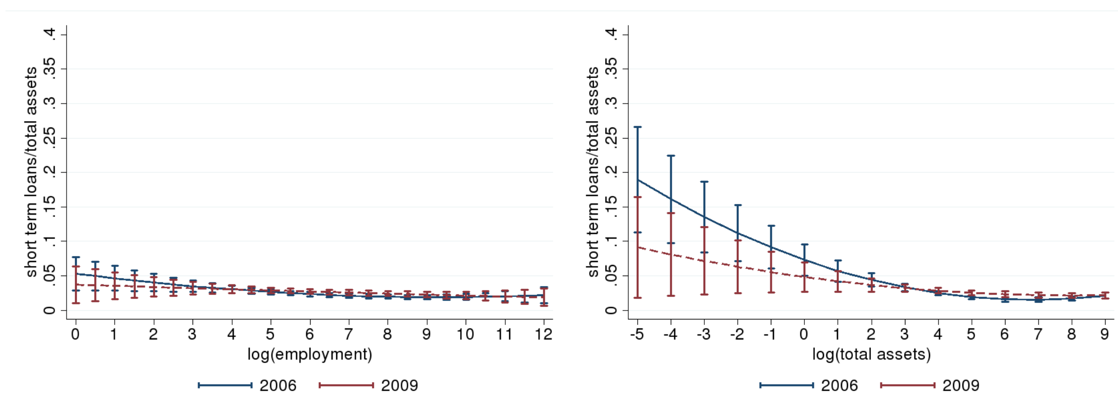
Consistent with our findings in section 2.4.3, the figures here show a positive relationship between short-term leverage and size among private firms that becomes significantly weaker during the Great Recession when size is measured by employment. In contrast, the relationship between leverage and size is negative among listed firms and we do not find a significant change in the strength of that relationship between 2006 and 2009, regardless of whether size is measured by employment or total assets.

Figure B.3: Conditional Relationship between short-term leverage and size for private firms (2006 & 2009)



Notes: Use unbalanced sample of private firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the conditional relationship between leverage, size (measured by employment in the left panel and total assets in the right figure), size squared, firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure B.4: Conditional Relationship between short-term leverage and size for public firms (2006 & 2009)



Notes: Use unbalanced sample of public firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the conditional relationship between leverage, size (measured by employment in the left panel and total assets in the right figure), size squared, firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

C: Appendix for Chapter 3

C.1 Firm Level Data (ENIA)

C.1.1 Panel Construction

I use data from the Encuesta Nactional Industrial Anual (ENIA), which is an annual survey of manufacturing establishments conducted by the *Instituto Nacional de Estadisticas (INE).* Since there is no information identifying whether establishments belong to multiunit firms, all of my analysis is done at the plant level. The survey includes all manufacturing plants that employ ten individuals or more; and collects information on industry, sales, intermediate inputs, employment, depreciation, and investment. My unbalanced panel contains on average 5,000 unique observations per year.

I have access to two vintages of the data. The first panel covers the period 1980 through 1999 and the second covers the period 1995 through 2007. Importantly, the firm identifiers differ across these two panels. In order to form the complete panel for 1980 through 2007, I use value added, gross value of production, total revenues, total employment, industry classification, number of days worker per year and region to match firms across the two panels in the overlapping years (1995 through 1999).

During the overlapping period (1995-1999) there are 6,946 unique establishments in the 1980-1999 panel and 7,399 unique establishments in the 1995-2007 panel. I identify around 99% of the establishments from the earlier panel and 92% of establishments in the later panel.

In total, there are 635 firms that appear in the new panel between 1995 and 1999 that I cannot identify in the old panel. I drop 314 of these firms from my sample because they appear in 1995 and therefore I cannot identify their age. The remaining firms are born (or appear in the new panel) in 1996 or after, and as such, I do not drop them. To ensure that the empirical evidence I report in the main text is not overly influenced by the inclusion of these firms, I performed several robustness checks. I generated figures for the dispersion of productivity and marginal products using only the old panel, then only the new panel, and using both. The trends evolution of all these measures is qualitatively similar in all cases. In particular, I consistently observe falling dispersion in the late 1980s to mid/late-1990s, rising dispersion in 1997/1998 and a slight decline in dispersion after 2001/2002.

C.1.2 Variable Construction

To construct the measures, I use industry classification, value added, labor input and capital stock. I assume that industries correspond to their three-digit ISIC revision 2 classification. Some firms switch industries, but it is possible that some of this switching reflect errors rather than real product changes. To take this possibility into account, I follow Oberfield (2013) and assign each plant its modal industry. The value added is reported in nominal terms, and where necessary I use three-digit industry price deflators to obtain real value added. I follow Oberfield (2013) and Greenstreet (2007) and measure labor input as total workers adjusted for number of days worked ($l_{ist} = (totworkers_{ist})(days/365)$). Since I do not observe the number of hours directly, l_{ist} is the closest I get to a measure of labor hours. The capital stock series presents a challenge. In 1980, 1981 and 1992-2007 the survey asks respondents to report their capital stock. Because it is unclear whether firms adjust these stocks for inflation each year, it is standard in the literature to generate the capital stock series using the perpetual inventory method instead.

ENIA breaks down the capital stock into buildings, machinery, vehicles and land. Consistent with the literature I incorporate only buildings, machinery and vehicles into the capital stock series. For firms that are born in 1980, 1981 or 1992-2007, I can use the first observed capital stock to initialize the series. However, for the many firms not born in these years I have to initialize the series in a different manner. Because the approach I use to initialize the capital stock of these firms is also applicable to firms born in any year, I choose to initialize the capital stock of all firms using the Greenstreet (2007) approach described below. I verified that this method of initialization didn't affect my results by calculating all dispersion measures using a mixed initialization approach (ie: when possible I initialized the series using the first reported capital stock and using Greenstreet (2007) otherwise). All of the results are qualitatively the same.

As mentioned, I use Greenstreet (2007) approach to initialize the capital stock using reported depreciation for each type of capital.

$$K_{i0}^{X} = (1-\delta)\left[\left({}^{D_{i0}}/_{\delta}\right) - \left({}^{I_{i0}^{X}}/_{2}\right)\right] + I_{i0}^{X} \tag{C.1}$$

where K_{i0}^{X} denotes the stock of capital type X at establishment age zero; δ is the depreciation rate (5% for buildings, 10% for machinery and 20% for vehicles, following Liu (1993)); D_{i0} is the reported depreciation at age zero for capital type X; and I_{i0}^{X} is investment. Subsequently, just as in the case where the initial capital stock is reported, I use the perpetual inventory method to construct the full capital stock series for each type of capital.

$$K_{it}^{X} = (1-\delta)\,K_{it-1}^{X} + I_{it}^{X} \tag{C.2}$$

I do not have industry-specific investment price deflators for each category. The best I can do is use a country-specific investment prices from the World Development Indicators to deflate the capital stock series. Since most of my focus is on within-industry dispersion using a country-specific investment deflator will not affect my results.

In 1980, 1981 and 1992-2007 firms report their capital stock. I compare the capital stock series generated by the perpetual inventory method with this reported capital stock series for the balanced sample of firms in two ways.

1. **Capital type contribution:** In the reported capital stock series, machines account for 69% of total capital stock, structures for 27%, and vehicles for 4%. The perpetual inventory capital stock breakdown is 70% machines, 27% structures and 3% vehicles.

2. **Correlations:** the correlations between the reported and generated capital

stock series for machines is 0.81, for structures is 0.85, and for vehicles is 0.27.

C.1.3 Data Cleaning

As a final step in the data construction, I drop establishment-year observations if capital stock, total labor, labor payments, days worked, sales, or value added are missing or non-positive. I also drop observations if reported depreciation is negative; and firms exit and reenter the panel more than once. I drop industries with very few firms or who belong to highly regulated industries, which leaves me with 20 out of 29 industries. Although the survey is intended to cover establishments with 10 employees or more, about 5% of observations report below this threshold. I only drop establishments (not establishment-year) if the reported employment never exceeds over 10 workers. I also drop observations in the 0.1st and 99.9th percentiles of value added, capital stock and total workers.

C.1.4 Investment Rate and Labor Growth Rate

I construct investment separately for three types (X) of capital structures ($X = S$), equipment (E) and vehicles (V) :

$$I_{it}^X = PN_{it}^X + PU_{it}^X + RI_{it}^X + VI_{it}^X - SU_{it}^X \tag{C.3}$$

where PN is the purchases of new capital, PU is the purchase of used capital, RI denotes reforms and improvements made by third parties, VI denotes the value of internally produced capital, and SU is sale of used capital. Total investment is:

$$I_{it} = I_{it}^{S} + I_{it}^{E} + I_{it}^{V} \tag{C.4}$$

For the labor growth series I use total labor adjusted for for number of days worked:

$$L_{it} = (totworkers_{it})(days/365) \tag{C.5}$$

The investment rate is:

$$IK_{it} = \frac{I_{it}}{0.5\,(K_{it} + K_{it-1})} \tag{C.6}$$

and the labor growth rate is:

$$GL_{it} = \frac{L_{it} - L_{it-1}}{0.5\,(L_{it} + L_{it-1})} \tag{C.7}$$

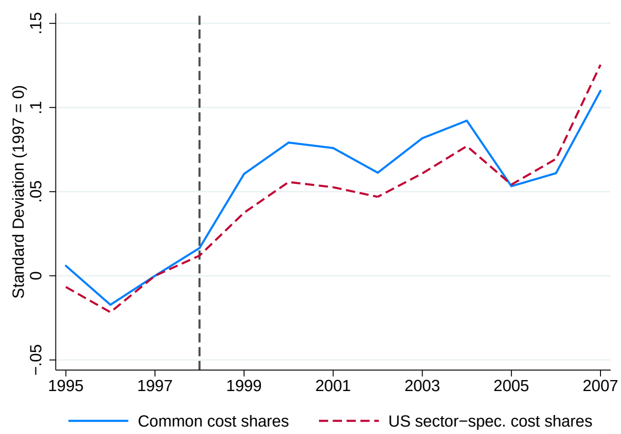
C.2 Alternative Cost Shares & Dispersion in Estimated Productivity

C.2.1 Alternative Cost Shares

When reporting the dispersion of $TFPR$ in figure 3.2 I assume that $\alpha_s = \alpha = 1/3$. This is done because Chile does not have data on industry-specific cost shares. Admittedly, the assumption is an extreme one because industries in Chile will have different cost shares. To make sure that the evolution of dispersion is not driven by this assumption I instead follow Hsieh and Klenow (2009) and set α_s as one minus the U.S. labor share for each industry. This assumption is also an extreme one since it is unlikely that industries in Chile have the same cost shares as those in the United States. The comparison is merely meant to show that the dispersion measures are not strongly affected by how α_s is set across industries because the measure captures within-industry variation across firms.

The results reported earlier hold (see figure C.1). Under sector-specific cost shares, dispersion in $TFPR$ rises during the period of high interest rates, and remains persistently high during the mid-2000s. Moreover, under sector-specific shares, the rise in dispersion is smaller than that obtained using common cost shares. The spike in dispersion post-2005 is likely driven by the positive copper price shock experienced during this period.

Figure C.1: Dispersion in $TFPR$ using alternative cost shares



Notes: Author's calculations based on ENIA manufacturing sector data. Data is used for a balanced sample of firms that are present in the data between 1980 and 2007. The blue line depicts dispersion in productivity calculated common cost shares across sectors ($\alpha_s = \alpha = 1/3$. The dashed red line depicts the dispersion in productivity using industry-specific cost shares (α_s is one minus the U.S. labor share for each industry. In each case, dispersion is calculated as the standard deviation across firms in a particular industry-year and aggregated using time-invariant employment shares. The grey vertical line denotes the onset of the 1998 sudden stop.

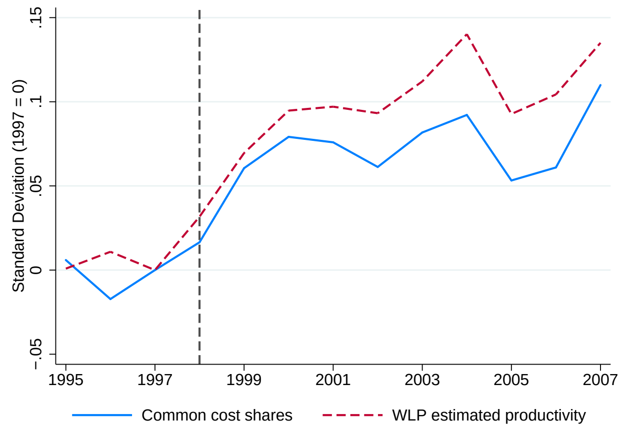
C.2.2 Dispersion in estimated productivity

The dispersion measures reported thus far are based on the Hsieh and Klenow (2009) framework, which assumes constant returns to scale. Here I report the evolution of dispersion in productivity using the Wooldridge (2009) extension of the Levinsohn and Petrin (2003) procedure. The estimation procedure is described in depth later in this section of the appendix. In short, the procedure uses GMM to estimate factor elasticities, and then uses these elasticities to obtain a measure of revenue productivity, which is distinct from the $TFPR$ measure reported earlier:

$$z_{ist} = y_{ist} - \left(\hat{\beta}_{ls} l_{ist} + \hat{\beta}_{ks} k_{ist}\right) \tag{C.8}$$

where s denotes the industry, z_{ist} is the estimated productivity, y_{ist} is value added, l_{ist} workers, k_{ist} is capital and $\hat{\beta}_{ls}$ and $\hat{\beta}_{ks}$ are the estimated elasticities. Figure C.2 shows that dispersion in WLP rises during the period of high interest rates and remains persistently high through the mid 2000s. Again, the rise in dispersion in WLP is more pronounced than the corresponding rise in dispersion of $TFPR$. It appears that the rise in dispersion in productivity is not sensitive to the assumption of common cost shares or the Hsieh and Klenow (2009) framework.

Figure C.2: Dispersion in $TFPR$ & WLP productivity



Notes: Author's calculations based on ENIA manufacturing sector data. Data is used for a balanced sample of firms that are present in the data between 1980 and 2007. The blue line depicts dispersion in productivity calculated common cost shares across sectors ($\alpha_s = \alpha = 1/3$. The dashed red line depicts the dispersion in productivity using productivity estimated through the Wooldridge (2009) extension of Levinsohn and Petrin (2003). In each case, dispersion is calculated as the standard deviation across firms in a particular industry-year and aggregated using time-invariant employment shares. The grey vertical line denotes the onset of the 1998 sudden stop.

C.2.3 Cost Shares and Production Function Estimation

The primary difference between the measures presented above and those in figure 3.2 are the elasticities used in deriving productivity. Table C.1 shows the factor elasticities used across the three approaches. Note first that I calculate all measures at the two digit industry level because the coverage of several three-digit industries is very thin when using the balanced sample of firms.

First, note that the weighted average estimated labor revenue elasticity is 0.52 and the capital revenue elasticity is 0.20. If I assume that the elasticity of substitution arising from downward sloping demand is equal to 4, as I do in my model, then these elasticities correspond to $1 - \hat{\alpha} = 0.69$ and $\hat{\alpha} = 0.27$, which are closer to the common elasticities I use in the empirical section than the U.S. cost shares. Further, while not exact, the estimated elasticities are quite close to the elasticities currently used in the model.

Table C.1: Cost Shares & Estimated Elasticities

	Common		US cost shares		Estimated	
Industry	$1-\alpha$	α	$1-\alpha_s^{US}$	α_s^{US}	$\hat{\beta}_{sl}$	$\hat{\beta}_{sk}$
31	0.67	0.33	0.18	0.82	0.50	0.20
32	0.67	0.33	0.38	0.62	0.51	0.19
33	0.67	0.33	0.41	0.59	0.45	0.21
34	0.67	0.33	0.34	0.66	0.54	0.19
35	0.67	0.33	0.28	0.72	0.52	0.16
36	0.67	0.33	0.38	0.62	0.58	0.16
38	0.67	0.33	0.37	0.63	0.52	0.25

Notes: Author's calculations based on ENIA manufacturing sector data. Data are used for a balanced sample of firms that are present in the data between 1980 and 2007. The table reports the labor and capital elasticities using common cost shares, US industry-specific cost shares, and elasticities estimated through the Wooldridge (2009) extension of Levinsohn and Petrin (2003).

C.2.4 Estimation: Wooldridge Extension of Levinsohn and Petrin

In addition to measuring productivity using ($TFP_{is} = \left(\frac{(P_sY_s)^{-\frac{1}{\varepsilon-1}}}{P_s}\right)\left(\frac{(p_{is}y_{is})^{\frac{\varepsilon}{\varepsilon-1}}}{k_{is}^{\alpha}l_{is}^{1-\alpha}}\right)$, as in Hsieh and Klenow (2009)), I also estimate the productivity process using the Wooldridge (2009) extension of Levinsohn and Petrin (2003). The estimation code is available online on Petrin's website and I implement it with the slight modification that I incorporate year fixed effects as suggested in Gopinath et al. (2017). The basic procedure is described below. Note that below I describe the estimation for one industry s, but I implement the procedure for each industry so that the estimated elasticities are sector-specific.

Initial choices:

1. I first choose the form of the production function.

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + z_{it} + \varepsilon_{it} \tag{C.9}$$

   All of the variables are in log, and y_{it} is value added, l_{it} is labor, and k_{it} is capital

2. Choose proxy variable: I choose m_{it}, which is materials.

3. Lags for the instrumental variable: I choose a one period lag

I'm going to describe the method/psuedo-code for the case described above

1. The production technology is assumed to be:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + z_{it} + \varepsilon_{it} \tag{C.10}$$

2. Let's suppose that materials is the proxy variable for k_{it} . Then the equation above can be rewritten as

$$y_{it} = \beta_l l_{it} + h\left(k_{it}, m_{it}\right) + \varepsilon_{it} \tag{C.11}$$

   where $h\left(k_{it}, m_{it}\right) = \alpha + \beta_k k_{it} + g\left(m_{it}, k_{it}\right)$

3. $g\left(m_{it}, k_{it}\right)$ is assumed to be well approximated by a third-order polynomial (this was first done in LP and it seems that is has become standard):

$$g\left(m_{it}, k_{it}\right) = \sum_{i=0}^{3}\sum_{j=0}^{3-i} \delta_{ij} k_t^i m_t^j \tag{C.12}$$

In the code each component of that sum is generated as a new variable.

4. The term, $f\left[g\left(k_{it-1}, m_{it-1}\right)\right]$ is related to the following equations:

$$y_{it} = \alpha + \beta_l l_{it} + \beta k_{it} + \sum_{i=0}^{3}\sum_{j=0}^{3-i} \delta_{ij} k_t^i m_t^j + e_{it} \tag{C.13}$$

and

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + +f\left[\sum_{i=0}^{3}\sum_{j=0}^{3-i} \delta_{ij} k_t^i m_t^j\right] + u_{it} \tag{C.14}$$

5. From the above all of the coefficients are estimated using GMM. The code ends up being just one line using `ivreg2`.

   - The dependent variable is real value added
   - The exogenous variables are the components of $g\left(m_{it}, k_{it}\right)$
   - The endogenous variable is just l_{it}
   - And the instrumental variable is just l_{it-1} (it's an instrument for the endogenous variable).
   - Specify that GMM is being used and cluster at the firm level and include year fixed effects.
   - The regression is run by industry so you end up with estimates for β_l and β_k by industry.

6. After the estimates have been obtained, the productivity for each firm i at time t is obtained as the residual

$$z_{it} = y_{it} - \left(\hat{\beta}_l l_{it} + \hat{\beta}_k k_{it}\right) \tag{C.15}$$

C.3 Rederivation of Dixit (1995) and Calcagnini and Saltari (2000)

C.3.1 Setup

The following setup is common to both cases I consider:

1. Assume that there is a continuum of risk-neutral firms that differ in their productivity Z_{it}. When I consider interest rate level, Z_{it} represents transitory fluctuations in idiosyncratic productivity. When I consider stochastic interest rates, $Z_{it} = Z_i$ for all i. In this latter case, Z_i should be thought of as permanent productivity.

2. In the first case, when demand is stochastic, I assume that Z_{it} follows a simple geometric Brownian process:

$$dZ_{it} = \sigma_Z Z_{it} dW_t^z \tag{C.16}$$

where dW_t^z is a Wiener process with zero mean and unit variance. The process is an extreme one that assumes there is no persistence or drift in the transitory shock, but is appropriate here because I am only interested in the volatility of the process.

3. Firms discount net revenues at the riskless interest rate r_t. In the first case, $r_t = r$. In the second case the interest rate is stochastic and follows a Brownian process.

$$dr_t = \sigma_r r_t^{3/2} dW_t^r \tag{C.17}$$

where dW_t^r is also a Wiener process with zero mean and unit variance. The process (C.17) is chosen because it allows me to derive analytical results. It is also used in Calcagnini and Saltari (2000).

4. The law of motion for capital is given by:

$$dK_{it} = I_{it} d_t \tag{C.18}$$

This formulation assumes no depreciation, which enables me to obtain analytical results in the case of stochastic interest rates.

5. Investment is assumed to be fully irreversible. Formally, I impose:

$$I_{it} \geq 0 \tag{C.19}$$

This is an extreme case of partial irreversibility. I choose it because it allows me to solve for one threshold instead of two, and the results are qualitatively similar to those I would obtain with partial irreversibility.[1]

6. The firm's reduced form profits are given by:

[1] Abel and Eberly (1996) show that when investment is partially irreversible, the investment policy is characterized by two thresholds – one below which firms disinvest and the other above which firms invest. In between these two thresholds lies the inaction region.

$$\Pi_{it} = \frac{Z_{it}^{\eta} K_{it}^{1-\eta}}{1-\eta} \tag{C.20}$$

Where $\eta < 1$. As in the previous section, (C.20) should be thought of as representing a firm operating a constant returns to scale production technology and facing a downward sloping demand curve.

7. Each firm i maximizes the present discounted value of its net profits:

$$V\left(Z_{it}, K_{it}, r_t\right) = \max_{I_{it} \geq 0} E_t \left[\int_t^{\infty} e^{-\int_t^s r(u)du} \left(\Pi_{it} - I_{it}\right)\right] \tag{C.21}$$

In this section I characterize the investment policy of an individual firm. As a result, firm heterogeneity only matters in as much as firms with different values of Z_{it} will either lie below or above the investment threshold.

8. Note that for this analysis I abstract from the time-to-build assumption, which means that investment becomes immediately productive. As a result, in the absence of any adjustment costs the firm's problem is equivalent to static profit maximization. In this case, as Jorgenson (1963) establishes, $MRPK_{it} = r$.

C.3.2 Case 1: Interest Rate Level

In case 1 the interest rate is deterministic and uncertainty only arises from fluctuations in idiosyncratic productivity.Applying Ito's Lemma to the (C.21) I obtain:

$$rV\left(Z_{it},K_{it}\right)=\max_{I_{it}\geq 0}\left\{\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta}-I_{it}+I_{it}V_K\left(Z_{it},K_{it}\right)+\frac{\sigma_z^2}{2}Z_{it}^2V_{zz}\left(Z_{it},K_{it}\right)\right\} \tag{C.22}$$

Firms that invest satisfy the following standard first order condition:

$$V_k=1 \tag{C.23}$$

The irreversibility assumption generates a region of inaction in which firms find it optimal to delay investment. When this is the case, $I_{it}=0$ and (C.22) becomes:

$$-\frac{\sigma_z^2}{2}Z_{it}^2V_{zz}\left(Z_{it},K_{it}\right)+rV\left(Z_{it},K_{it}\right)=\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta} \tag{C.24}$$

Equation (C.24) is a Cauchy-Euler non-homogenous second-order differential equation. The solution takes the standard form:

$$V=V_p+V_c \tag{C.25}$$

Let's start by finding the particular solution (V_p), which represents the firm's expected present value of net profits in the absence of frictions or any future investment. Using guess and verify:

$$\text{Guess: } V=X\left(\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta}\right) \tag{C.26}$$

$$\text{Plug in: } rX\left(\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta}\right)-\frac{\sigma_z^2}{2}\eta\left(\eta-1\right)X\left(\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta}\right)=\frac{Z_{it}^{\eta}K_{it}^{1-\eta}}{1-\eta} \tag{C.27}$$

$$\text{Solve for } X\text{: } X=\frac{1}{r-\frac{\sigma_Z^2}{2}\eta\left(\eta-1\right)} \tag{C.28}$$

Putting these together I obtain:

$$V_p = \left(\frac{1}{r - \frac{\sigma_x^2}{2}\eta\left(\eta - 1\right)} \right) \left(\frac{Z_{it}^{\eta} K_{it}^{1-\eta}}{1-\eta} \right) \tag{C.29}$$

Notice that since V_p is concave in Z_{it} and $\eta < 1$, an increase in σ_z lowers V_p and therefore lowers desired investment. When σ_z is high, the probability of very low and very high realizations of Z_{it} increases. Since V_p is concave in Z_{it}, the cost of low realizations of Z_{it} outweigh the benefits of high realizations. Further, an increase in r also lowers V_p because it raises the cost of capital, and therefore also lowers desired investment. Next, I findV_c, which captures the effect of the lower bound on investment. Technically, it is the solution to the characteristic equation of the second order differential equation (C.24):

$$V_c = C_p\left(K_{it}\right) Z_{it}^{s_p} + C_n\left(K_{it}\right) Z_{it}^{s_n} \tag{C.30}$$

Note that in (C.30), the coefficients C_p and C_n are functions of K_{it}; s_p and s_n are the positive and negative roots, respectively, of the characteristic equation:

$$f\left(s\right) = -\frac{\sigma_Z^2}{2}s^2 + \frac{\sigma_Z^2}{2}s + r = 0 \tag{C.31}$$

$$s_{p/n} = \frac{-\frac{\sigma_Z^2}{2} +/- \sqrt{\left(\frac{\sigma_Z^2}{2}\right)^2 + 2\sigma_Z^2 r}}{\sigma_Z^2} \tag{C.32}$$

I can simplify (C.30). Since irreversible investment represents a one-sided barrier, either C_p or C_n will be zero. Noting that V is increasing in Z_{it}, I impose $C_n = 0$.

$$V = \left(\frac{1}{r - \frac{\sigma_x^2}{2}\eta\left(\eta - 1\right)} \right) \left(\frac{Z_{it}^{\eta} K_{it}^{1-\eta}}{1-\eta} \right) + C_p\left(K_{it}\right) Z_{it}^{s_p} \tag{C.33}$$

Recall that the first term represents the present value of net profits in the absence of future investment, while the second term represents the effect of the irreversibility friction.

Equation (C.33) contains two unknowns: C_p and a threshold $\bar{Z}_{it}$ at which the firm is indifferent between investing and not investing. To solve for the unknowns I use the *value-matching*and *smooth-pasting* conditions evaluated at $\bar{Z}_{it}$, which are respectively given by:

$$V_k = \left(\frac{1}{r - \frac{\sigma_x^2}{2}\eta\left(\eta - 1\right)}\right)\left(\bar{Z}_{it}^{\eta} K_{it}^{-\eta}\right) + C_{pK}\left(K_{it}\right)\bar{Z}_{it}^{s_p} = 1 \tag{C.34}$$

$$V_{kz} = \frac{\eta \bar{Z}_{it}^{\eta-1} K_{it}^{-\eta}}{r - \frac{\sigma_x^2}{2}\eta\left(\eta - 1\right)} + s_p C_{pK}\left(K_{it}\right)\bar{Z}_{it}^{s_p - 1} = 0 \tag{C.35}$$

(C.34) states that at $\bar{Z}_{it}$ the value of not investing (LHS) and investing (RHS) must be equal. (C.35) states that the two value functions must join smoothly at $\bar{Z}_{it}$. Since I am only interested in the value of the threshold $\bar{Z}_{it}$, I multiply both sides of (C.35) by $\bar{Z}_{it}$ and solve for $C_{pK}\left(K_{it}\right)\bar{Z}_{it}^{s_p}$. Plugging the result into (C.34) and solving for $\bar{Z}_{it}$:

$$\bar{Z}_{it} = \left(\frac{\left(r - \frac{\sigma_z^2}{2}\eta\left(\eta - 1\right)\right)s_p}{\left(s_p - \eta\right)K_{it}^{-\eta}}\right)^{1/\eta} \tag{C.36}$$

Expression (C.36) can be simplified further using the insight of Abel and Eberly (1996). Observe the following

$$f\left(\eta\right) = -\frac{\sigma_Z^2}{2}\eta^2 + \frac{\sigma_Z^2}{2}\eta + r = -\frac{\sigma_z^2}{2}\left(\eta - s_p\right)\left(\eta - s_n\right) \tag{C.37}$$

$$s_p s_n = -\frac{2r}{\sigma_z^2} \tag{C.38}$$

$$(\eta - s_p)(\eta - s_n) = -\frac{2f(\eta)}{\sigma_z^2} \tag{C.39}$$

$$\frac{r(\eta - s_p)(\eta - s_n)}{s_p s_n} = f(\eta) \tag{C.40}$$

Using these results in C.36, $\bar{Z}$ takes the more intuitive form:

$$\bar{Z}_{it} = \left[\frac{r}{K_{it}^{-\eta}}\left(1 - \frac{\eta}{s_n}\right)\right]^{1/\eta} \tag{C.41}$$

This threshold denotes the value of Z_{it} below which firms do not invest. Above $\bar{Z}_{it}$ firms satisfy (C.42). Since s_n is negative, it is clear that irreversibility raises the user cost of capital relative to the frictionless case by a factor of $\left(1 - \frac{\eta}{s_n}\right)$.

$$Z_{it}^{\eta} K_{it}^{-\eta} = MRPK_{it} = \left[r\left(1 - \frac{\eta}{s_n}\right)\right] \tag{C.42}$$

Next I explore how the threshold (C.41) responds to changes in the interest rate r. For concreteness, I consider numerical examples in which I assign the following parameter values:

- $K = 2$; $\eta = 0.5$
- I vary the interest rate r from $r_1 = 10\%$ to $r_2 = 20\%$

In deriving $\frac{\partial \bar{Z}}{\partial r}$, I first need to know the sign of $\frac{\partial s_n}{\partial r}$:

- $\frac{\partial s_n}{\partial r} = -\frac{2}{\sqrt{\left(-\frac{\sigma_Z^2}{2}\right)^2 + 2\sigma_Z^2 r}} < 0$

Turning now to the effect of changes the interest rate level on the threshold $(\bar{Z})$:

$$\frac{\partial \bar{Z}}{\partial r} = \frac{\left(\eta r \frac{\partial s_n}{\partial r} - \eta s_n + s_n^2\right)\left[\frac{r}{K_{it}^{\eta}}\left(1 - \frac{\eta}{s_n}\right)\right]^{1/\eta - 1}}{\eta K_{it}^{-\eta} s_n^2} > 0 \tag{C.43}$$

There are two opposing forces at play. The interest rate affects the threshold directly through the Jorgenson (1963) user cost of capital (r) and indirectly through the option value. The direct effect pushes the threshold higher because the incentive to invest falls with higher costs. The indirect effect is negative and pushes the threshold lower because when firms discount the future at a higher rate, the option value of waiting to take action falls. The direct effect dominates the indirect effect. A rise in the interest rate results in an expansion of the inaction region.

$\sigma_Z^2 = 0.02$		
r	$\left(1 - \frac{\eta}{s_n}\right)$	$\bar{Z}_{it}$
0.1	1.14	0.0258
0.2	1.10	0.0968

Notes: Through a numerical exercise, the last column shows that as interest rates rise (first column) the threshold for investment increases (last column).

C.3.3 Case 2: Interest Rate Volatility

In the second case I impose that $Z_{it} = Z_i$ (i.e. that each firm's productivity is permanent), and that the stochastic interest rate follows (C.17). Applying Ito's Lemma to (C.21) results in the following Hamiltonian-Jacobi-Bellman equation:

$$r_t V\left(Z_i, K_{it}, r_t\right) = \max_{I_{it} \geq 0} \left\{ \frac{Z_i^{\eta} K_{it}^{1-\eta}}{1-\eta} - I_{it} + I_{it} V_k\left(Z_i, K_{it}, r_t\right) + \frac{\sigma_r^2}{2} r^3 V_{rr}\left(Z_i, K_{it}, r_t\right) \right\} \tag{C.44}$$

Just as in case 1, the presence of irreversibility induces some firms to delay investment. Firms that do invest ($I_{it} > 0$) satisfy $V_k = 1$. For firms that do not invest ($I_{it} = 0$), equation (C.44) becomes:

$$-\frac{\sigma_z^2}{2} r^3 V_{rr}\left(Z_i, K_{it}, r_t\right) + rV\left(Z_i, K_{it}, r_t\right) = \frac{Z_i^{\eta} K_{it}^{1-\eta}}{1-\eta} \tag{C.45}$$

To transform (C.46) into a linear second-order differential equation I divide through by r:

$$-\frac{\sigma_z^2}{2} r^2 V_{rr}\left(Z_i, K_{it}\right) + V\left(Z_i, K_{it}\right) = \frac{Z_i^{\eta} K_{it}^{1-\eta}}{r\left(1-\eta\right)} \tag{C.46}$$

The general solution to (C.46) takes the form:

$$V = V_p + V_c \tag{C.47}$$

To solve for V_p I use guess and verify:

$$\text{Guess: } V_p = X \frac{Z_i^{\eta} K_{it}^{1-\eta}}{r\left(1-\eta\right)} \tag{C.48}$$

$$\text{Plug in: } -\frac{\sigma_r^2}{2} r^2 \left(\frac{2X}{r^3}\right)\left(\frac{Z_i^{\eta} K_{it}^{1-\eta}}{(1-\eta)}\right) + \left(\frac{X}{r}\right)\left(\frac{Z_i^{\eta} K_{it}^{1-\eta}}{(1-\eta)}\right) = \left(\frac{1}{r}\right)\left(\frac{Z_i^{\eta} K_{it}^{1-\eta}}{(1-\eta)}\right) \tag{C.49}$$

$$\text{Solve for } X\text{: } X = \frac{1}{\left(1-\sigma_r^2\right)} \tag{C.50}$$

The particular solution captures the present discounted value of the firm's net profits in the absence of frictions and future investment.

$$V_p = \left(\frac{1}{r\left(1-\sigma_r^2\right)}\right)\left(\frac{Z_i^{\eta} K_{it}^{1-\eta}}{1-\eta}\right) \tag{C.51}$$

If investment were fully irreversible $V = V_p$ and $MRPK$ could be expressed as:

$$V_k = MRPK_{it} = Z_i^{\eta} K_{it}^{-\eta} = r\left(1-\sigma_r^2\right) \tag{C.52}$$

As σ_r^2 approaches zero, $MRPK$ approaches the standard Jorgenson (1963) user cost r. The presence of σ_r^2 lowers $MRPK$ and raises desired investment. High interest rate volatility raises the probability of very low and very high realizations of the interest rate; and the convexity of V_p in r means the benefits from the low realizations offset the costs from the high realizations.

Returning now to the general solution, I solve for V_c:

$$V_c = C_p (K_{it}) r^{s_p} + C_n (K_{it}) r^{s_n} \tag{C.53}$$

Note again that the coefficients C_p and C_n are not constants, but depend on K_{it} and parameters (which in the case of permanent productivity also includes Z_i). s_p and s_n are the positive and negative roots of the characteristic equation:

$$f(s) = -\frac{\sigma_r^2}{2} s^2 + \frac{\sigma_r^2}{2} s + 1 = 0 \tag{C.54}$$

the solution of which is given by:

$$s_{p/n} = {}^1\!/_2 {}^+\!/_- \sqrt{{}^1\!/_4 + {}^2\!/_{\sigma_r^2}} \tag{C.55}$$

Since irreversible investment represents a one-sided barrier, and the firm's value is decreasing in r, I simplify (C.53) by imposing $C_p = 0$. As a result, (C.47) becomes:

$$V = \frac{Z_i^{\eta} K_{it}^{1-\eta}}{r (1 - \sigma_r^2) (1 - \eta)} + C_n (K_{it}) r^{s_n} \tag{C.56}$$

The second term in (C.56) represents the option value of future investment opportunities. To find C_n and the threshold $\bar{r}$ I use the *value-matching* and *smooth-*

pasting conditions evaluated at $\bar{r}$:

$$V_k = \frac{Z_i^\eta K_{it}^{-\eta}}{\bar{r}\left(1-\sigma_r^2\right)} + C_{nK}\left(K_{it}\right)\bar{r}^{s_n} = 1 \tag{C.57}$$

$$V_{kr} = -\frac{Z_i^\eta K_{it}^{-\eta}}{\bar{r}^2\left(1-\sigma_r^2\right)} + s_n C_n\left(K_{it}\right)\bar{r}^{s_n-1} = 0 \tag{C.58}$$

(C.57) states that at $\bar{r}$ the value of not investing (LHS) and investing (RHS) must be equal. (C.58) states that at the threshold $\bar{r}$ the two value functions must join smoothly. Solving the system I obtain the following $\bar{r}$:

$$\bar{r} = Z_i^\eta K_{it}^{-\eta}\left(\frac{s_n+1}{s_n\left(1-\sigma_r^2\right)}\right) \tag{C.59}$$

A firm characterized by (Z_i, K_{it}) invests only if the interest rate r is below $\bar{r}$. Those firms that do invest satisfy:

$$Z_i^\eta K_{it}^{-\eta} = \left(\frac{s_n}{s_n+1}\right) r\left(1-\sigma_r^2\right) \tag{C.60}$$

If a firm characterized by $\left(z_i^P, K_{it}\right)$ observes an interest rate above $\bar{r}$ it will not invest. Since $\left(\frac{s_n}{s_n+1}\right) > 1$, irreversibility raises $MRPK$ and lowers desired investment relative to the frictionless case (C.52). Next I look at how the threshold $\bar{r}$ responds to changes in σ_r^2. Note that interest rate volatility affects the threshold (C.59) directly through σ_r^2 and indirectly through s_n. The direct effect is positive, meaning that firms are willing the invest at a higher interest rate. The indirect is negative, meaning that firms require a lower interest rate to invest. Below I show that the negative effect dominates.[2] For concreteness I fix the following parameters

[2]The negative effect does not always dominate. Alvarez and Koskela (2006) shows that if the interest rate process evolves according to the Cox et al. (1985) model – $dr_t = (a - br_t)\,dt + \sigma\sqrt{(r_t)}dW_t$– the effect of interest rate volatility is ambiguous. Importantly, when he considers a mean reverting process (which is similar to a discrete-time $AR(1)$ process that we generally use)

and verify some of the results below numerically:

- $K = 2$; $\eta = 0.5$; and $z_i^P = 1$

- I vary the volatility parameter σ_r^2 from $\sigma_r^2 = 0.06$ to $\sigma_r^2 = 0.08$

  In deriving $\frac{\partial \bar{r}}{\partial \sigma_r^2}$, I first need to know the sign of $\frac{\partial s_n}{\partial \sigma_r^2}$:

- $\frac{\partial s_n}{\partial \sigma_r^2} = \frac{2}{\sigma_r^4 \sqrt{\frac{1}{4}+\frac{2}{\sigma_r^2}}} > 0$ Therefore, an increase in interest rate volatility raises the value of keeping the investment option open and delaying investment.

  Turning to $\frac{\partial \bar{r}}{\partial \sigma_r^2}$:

$$\frac{\partial \overline{r}}{\partial \sigma_r^2} = \frac{Z_i^\eta K_{it}^{-\eta}}{\left(1-\sigma_r^2\right)^2} \left(\frac{s_n+1}{s_n}\right) - \frac{Z_i^\eta K_{it}^{-\eta}}{\left(1-\sigma_r^2\right)} \left(\frac{1}{s_n^2} \frac{\partial s_n}{\partial \sigma_r^2}\right) \tag{C.61}$$

$$\frac{\partial \overline{r}}{\partial \sigma_r^2} = \frac{Z_i^\eta K_{it}^{-\eta}}{s_n^2 \left(1-\sigma_r^2\right)^2} \left(s_n \left(s_n+1\right) - \frac{1-\sigma_r^2}{\sigma_r^4 \sqrt{\frac{1}{4}+\frac{2}{\sigma_r^2}}}\right) \tag{C.62}$$

(C.62) can be simplified by referring to the definition of s_n:

$$1 - \sigma_r^2 = \frac{s_n^2 - s_n - 2}{s_n^2 - s_n} \tag{C.63}$$

$$\sigma^4 = \frac{4}{s_n^4 - 2s_n^3 + s_n^2} \tag{C.64}$$

$$\sqrt{\frac{1}{4}+\frac{2}{\sigma_r^2}} = \left(\frac{1}{2} - s_n\right) \tag{C.65}$$

$$\frac{1-\sigma_r^2}{\sigma_r^4 \sqrt{\frac{1}{4}+\frac{2}{\sigma_r^2}}} = \left(\frac{s_n^2 - s_n - 2}{s_n^2 - s_n}\right) \left(\frac{s_n^4 - 2s_n^3 + s_n^2}{4}\right) \left(\frac{2}{1-s_n}\right) \tag{C.66}$$

This last equation simplifies to:

$$\frac{1-\sigma_r^2}{\sigma_r^4 \sqrt{\frac{1}{4}+\frac{2}{\sigma_r^2}}} = \frac{\left(s_n^2 - s_n - 2\right)\left(s_n^2 - s_n\right)}{2\left(1-s_n\right)} \tag{C.67}$$

– $dr_t = ar_t\left(1-br_t\right)dt + \sigma r_t dW_t$– the negative effect of interest rate volatility on the threshold dominates.

Plugging (C.67) into (C.62):

$$\frac{\partial \overline{r}}{\partial \sigma_r^2} = \frac{Z_i^{\eta} K_{it}^{-\eta}}{s_n^2 \left(1-\sigma_r^2\right)^2} \left[\frac{s_n \left(s_n+1\right)\left(2-4s_n\right) - \left(s_n^2 - s_n - 2\right) s_n \left(s_n - 1\right)}{2-4s_n} \right] \tag{C.68}$$

which becomes:

$$\frac{\partial \overline{r}}{\partial \sigma_r^2} = \frac{Z_i^{\eta} K_{it}^{-\eta}}{s_n^2 \left(1-\sigma_r^2\right)^2} \left[\frac{-s_n^2 \left(s_n+1\right)^2}{2-4s_n} \right] < 0 \tag{C.69}$$

Equation (C.69) indicates that as interest rate volatility rises, the threshold value of the interest rate at which firms are willing to invest falls (i.e. firms require a lower interest rate before they are willing to invest). One the one hand, when interest rate volatility rises firms want to invest more because the gains from low realizations of the interest rate will outweigh the losses from high realizations (direct effect). On the other hand, higher interest rate volatility raises the opportunity cost of investing, thus generating an incentive to delay investment (indirect effect). Since the indirect effect dominates in this case, a rise in interest rate volatility lowers $\bar{r}$.

From the point of view of a firm that is characterized by (Z_i, K_{it}) a single interest rate r prevails in the economy. When deciding whether or not to invest, each firm checks whether this r lies below or above $\bar{r}$. The result in the section shows that keeping the level of r constant and raising σ_r^2 will cause more firms to fall into the investment inaction region.

The results from case 1 and case 2 indicate that 1) an increase in the interest rate level and 2) an increase in interest rate volatility induce more firms to delay investment, and are thus associated with an expansion of the inaction region.

C.4 Model Solution

The model is parametrized according to section 5.3. I use value function iteration to solve the model.

Table C.2: Parameter Values

δ_k	δ_l	κ	λ	w	ρ_A	$100\sigma_A$	$\bar{R}$	ρ_R	$100\sigma_R$	$100\bar{\sigma}_\sigma$	ρ_σ	$100\sigma_\sigma$	P_k	P_l	ρ_z	$100\sigma_z$
2.5%	8%	0.25	0.50	1	0.95	1.75	1.015	0.84	0.32	0.32	0.455	0.30	0.38	0.266	0.765	0.17

Notes: The parameter values are reported for the baseline model. The model is calibrated at a quarterly frequency.

1. **Grid points:**

   (a) **Exogenous state variables:** I use 5 grid points for idiosyncratic productivity (z), which evolves according to an $AR(1)$ process. The interest rate also evolves according to an $AR(1)$ process, but I fix the minimum and maximum values of the R grid based on the lowest and highest real interest rates I observe in the data. The smallest value is 1.0039 and the highest is 1.036. I use 5 grid points for the interest rate. Interest rate volatility also evolves according to an $AR(1)$ process. I use 2 grid points for volatility and fix the low value to equal the long run mean ($\bar{\sigma}_\sigma$) and the high value to equal the realized volatility at the onset of the crisis in 1998:Q3 (0.014). Aggregate productivity/demand (A) evolves according to an $AR(1)$ and I discretize the grid, allowing for 3 grid points, and compute the transition matrix using the Tauchen method.

(b) **Endogenous state variables:** I pick the minimum and maximum grid points for both l and k such that the firms never choose the boundary points. Because l represents hours its state space is bounded between 0 and 1. I choose 68 grid points for l and 200 grid points for k. I use log-linear spacing so that grid points are concentrated at the lower end. Moreover, I incorporate depreciation into the grid so that the choice of no investment and no hiring can be made on the grid. This trick (used in Bloom et al. (2018)) is extremely helpful computationally as it makes the model with three exogenous states, two endogenous states, and two kinks in each policy function arising from non-convex adjustment costs in both labor and capital, tractable to solve.

2. **Value function iteration:**

   (a) **Standard:** the value function iteration is standard and I use a Howard policy iteration loop to speed up convergence.

   (b) **Convergence:** I set the tolerance parameter for convergence at 1.e-6 and iterate until the value function converges. Usually the policy function converges well before the value function does, but I require the value function to converge before exiting the value function iteration loop.

3. **Unconditional simulation:**

   (a) **Simulation:** when calibrating parameters I run an unconditional simulation of 5,004 periods, with a burn in of 4,884 periods. This leaves a total of 120 periods, or 30 years, which is consistent with the length of my balanced panel (28 years). Each period is characterized by an aggregate exogenous state given by (A, R, V), where A denotes the realization of aggregate productivity/demand, R denotes the realization of the real interest rate and V denotes the realization of interest rate volatility.

(b) **Calibration:** when calibrating the model, I simulate the aggregate process as described above, along with a sample of 1,000 establishments to whom I assign productivity values according to the $AR(1)$ process for idiosyncratic productivity. Since the model is solved at a quarterly frequency, I use the simulated panel of firms to aggregate observables to an annual frequency and generate the model moments that I compare to data moments for calibration.

4. **Impulse responses:**

(a) **Shocks:** I consider the economy's response to two shocks, interest rate level and interest rate volatility. I do a simulation of 101 periods and impose the shock in the 45th period. When I consider an interest rate level shock, interest rate volatility evolves normally. When I consider an interest rate volatility shock I let the interest rate level evolve normally (i.e. the interest rate volatility shock does not generate a rise in the interest rate).

(b) **Simulation:** I begin the simulation at the stochastic steady state distribution, the middle of the A and R processes and at low interest rate volatility. I simulate 2,000 economies over 101 periods. Each of the economies has two copies. One copy may experience the shock and the other will never experience the shock. I say that the economy may experience the shock because in order to generate an R level shock of a similar magnitude as the sudden stop episode I first find the probability with which each of the 2,000 economies experiences the shock such that the average increase in the interest rate across all economies is equal to this magnitude. I only consider shocks to R and interest rate volatility. I leave a comparison of the IRFs to these shocks with IRFs to an A shock for future research.

(c) **Impulse Response:** once the simulation is complete, I compute the impulse responses as the deviation of the copy of each economy that may experience the shock from the copy of the economy that does not experience it. The impulse response is generated as the average across all the economies after discarding 200 of the economies.

C.5 Construction of Real Interest Rate for Chile

The EMBI spread for Chile is only available beginning in June 1999. In order to produce the series for November 1994 through May 1999 (for figure 3.1), I follow the procedure in Ates and Saffie (2016). I first regress the EMBI Chile spread on the EMBI spread for South Africa, which was chosen for its high correlation (0.92) with Chile's EMBI. Data for South Africa's EMBI are available beginning in November

1994. I use the regression results to generate a predicted EMBI Chile series and calculate the changes in the spread between periods in November 1994 and May 1999. EMBI Chile data are generated between 1994 and 1999 by applying these growth rates to the existing series.

For calibration I construct the interest rate series for 1998:Q1 through 2015:Q4 using the same approach as above. However, I do not have EMBI spread data for South Africa during this period. Instead, for the regression I use EMBI spread data for Latin America. The resulting real interest rate series for calibration is highly correlated, with a correlation coefficient of 0.81, with the interest rate series presented in figure 3.1.

C.6 Alternative Targets for Calibrating the Productivity Process

I calibrate ρ_z and σ_z by running the following $AR(1)$ regression:

$$\log\left(\hat{Z}_{ist}\right) = d_i + d_t + \rho^D \log\left(\hat{Z}_{ist-1}\right) + u^z_{ist} \tag{C.70}$$

where d_i denotes firm fixed effects, d_t denotes year fixed effects, and $\hat{Z}_{ist}$ is given by:

$$\hat{Z}_{ist} = \frac{p_{ist} y_{ist}}{k_{ist}^{\kappa_s} l_{ist}^{\lambda_s}} \tag{C.71}$$

The current calibration assumes that $\kappa_s = \alpha_s \left(1 - {}^1\!/\!_\eta\right)$, $\lambda_s = (1 - \alpha_s)\left(1 - {}^1\!/\!_\eta\right)$, where $\eta = 4$ and $\alpha_s = \alpha = {}^1\!/\!_3$. In table C.3, I report the results for ρ^D and σ^D for two alternative measures of κ_s and λ_s. The baseline results are reported in the first column. In the second column are results based on α_s being one minus the

U.S. labor share for each industry. The last column uses κ_s and λ_s estimated using WLP. The results indicate that ρ^D and σ^D are similar across the three methods, and that the persistence of idiosyncratic productivity is quite low and its volatility is very high.

Table C.3: Alternative measures for ρ^D and σ^D

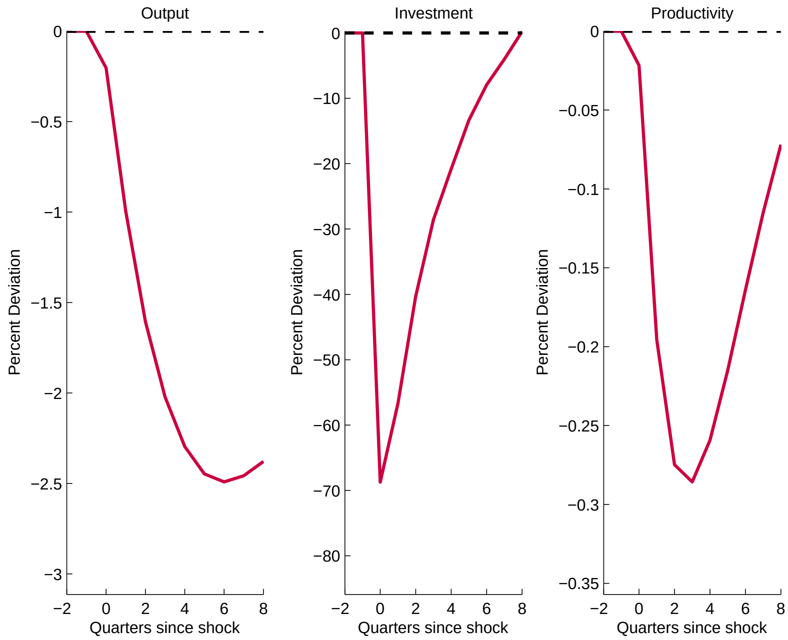
	Common α	U.S. sector-specific α	Estimated elasticity
ρ^D	0.42	0.49	0.49
σ^D	0.40	0.42	0.42

Notes: The table reports alternative calibrations for the parameters (p^D and σ^D) of the $AR(1)$ productivity process. The model is calibrate assuming common elasticities (second column). The third column reports the parameter estimates using US sector-specific elasticities. The last column reports the parameter estimates using elasticities estimated through the Wooldridge (2009) extension of Levinsohn and Petrin (2003).

C.7 Alternative IRF for interest rate level shock

In the main text I consider the impact of a one percentage point increase in the real interest rate. The resulting fall in output is under 2.5%, which is short of the 4% observed in the data. Assuming (and recognizing that this is a strong assumption) that the interest rate was wholly responsible for the fall in output, I now impose a 1.6 percentage points increase in the interest rate, which generates a 4% decline in output. A shock of this magnitude generates an extremely large, and implausible, fall in investment. It also strengthens the endogenous response of productivity, which now falls by 0.46%, which is still only about 1/9 of the decline observed in the data.

Figure C.3: Response to a Volatility Shock: Output, Investment and Hiring



Notes: The figure shows the IRFs in response to an interest rate level shock (1.6 percentage point) for output (left), investment (middle) and hiring (right). To produce the IRFs two versions of two economies are simulated for 100 periods each. In each of these economies, in one version the shock hits in the 45th period and in the second it does not. The IRFs are the cross-economy average percent differences between the shocked and unshocked simulations.

Bibliography

Abel, Andrew and Janice Eberly, "Optimal Investment with Costly Reversibility," *The Review of Economic Studies*, 1996, *63* (4), 581–593.

Acemoglu, Daron and Dan Vu Cao, "Innovation by Entrants and Incumbents," *Journal of Economic Theory*, 2015, *157*, 255–294.

_ and Fabrizio Zilibotti, "Was Prometheus Unbound by Chance? Risk, Diversification, and Growth," *Journal of Political Economy*, 1997, *105* (4), 709–751.

_ , Ufuk Akcigit, and Murat Celik, "Young, Restless and Creative: Openness to Disruption and Creative Innovations," 2017. Working Paper.

_ , _ , Haron Alp, Nicholas Bloom, and William Kerr, "Innovation, Reallocation and Growth," *American Economic Review*, forthcoming.

Aghion, Philippe and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica*, 1992, *60* (2), 323–351.

_ , Christopher Harris, Peter Howitt, and John Vickers, "Competition, Imitation, and Growth in Step-by-Step Innovation," *Review of Economic Studies*, 2001, *68* (3), 467–492.

_ , John van Reenen, and Luigi Zingales, "Innovation and Institutional Ownership," *American Economic Review*, 2013, *103* (1), 277–304.

Aguiar, Mark and Gita Gopinath, "Emerging Market Fluctuations: The Role of Interest Rates and Productivity Shocks," 2006. Tenth Annual Conference on the Central Bank of Chile, "Current Account and External Financing." Santiago, Chile: Central Bank of Chile.

Ajello, Andrea, "Financial Intermediation, Investment Dynamics, and Business Cycle Fluctuations," *American Economic Review*, 2016, *106* (8), 2256–2303.

Akcigit, Ufuk and William Kerr, "Growth through Heterogenous Innovation," *Journal of Political Economy*, 2018, *126* (4), 1374–1443.

___ , **Emin Dinlersoz, Jeremy Greenwood, and Veronika Penciakova**, "Synergizing Ventures," 2018. Working Paper.

___ , **Murat Celik, and Jeremy Greenwood**, "Buy, Keep, or Sell: Economic Growth and the Market for Ideas," *Econometrica*, 2016, *84* (3), 943–984.

Albuquerque, Rui and Hugo Hopenhayn, "Optional Lending Contracts and Firm Dynamics," *Review of Economic Studies*, 2004, *71* (2), 285–315.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin, "The Real and Financial Impact of Uncertainty Shocks," 2016. Unpublished draft, Stanford University.

Alizadeh, Sassan, Michael W. Brandt, and Francis X. Diebold, "Range-Based Estimation of Stochastic Volatility Models," *Journal of Finance*, 2002, *57* (3), 1047–1091.

Alvarez, Luis H. R., "Irreversible Capital Accumulation under Interest Rate Uncertainty," *Mathematical Methods of Operations Research*, 2010, *72* (2), 249–271.

___ **and Erkki Koskela**, "Irreversible Investment under Interest Rate Variability: Some Generalizations," *The Journal of Business*, 2006, *79* (2), 623–644.

Anderson, Ronald and David Reeb, "Founding-Family Ownership and Firm Performance: Evidence from the S&P 500," *The Journal of Finance*, 2003, *58* (3), 1301–1328.

Ang, James, Rebel Cole, and Daniel Lawson, "The Role of Owner in Capital Structure Decisions: An Analysis of Single-Owner Corporations," *Journal of Entrepreneurial Finance*, 2010, *14* (3), 1–36.

Asker, John, Allan Collard-Wexler, and Jan De De Loecker, "Dynamic Inputs and Resource (Mis)Allocation," *Journal of Political Economy*, 2014, *122* (5), 1013–1063.

___ , **Joan Farre-Mensa, and Alexander Ljungqvist**, "Corporate Investment and Stock Market Listing: A Puzzle?," *Review of Financial Studies*, 2015, *28* (2), 342–390.

Ates, Sina and Felipe Saffie, "Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection," 2016. International Finance Discussion Papers 1187.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta, "Cross-Country Differences in Productivity: The Role of Allocation and Selection," *American Economic Review*, 2013, *103* (1), 305–334.

Bassetto, Marco, Marco Cagetti, and Mariacristina De Nardi, "Credit Crunches and Credit Allocation in a Model of Entrepreneurship," *Review of Economic Dynamics*, 2015, *18* (1), 53–76.

Begenau, Juliane and Juliana Salomao, "Firm Financing over the Business Cycle," 2015. Working Paper.

Berger, Allen and Gregory Udell, "The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle," *Journal of Banking and Finance*, 1998, *22.*

Bergoeing, Raphael, Patrick Kehoe, Timothy Kehoe, and Raimundo Soto, "A Decade Lost and Found: Mexico and Chile in the 1980s," *Review of Economic Dynamics*, 2002, *5* (1), 166–205.

Bernanke, Ben and Mark Gertler, "Agency Costs, Net Worth and Business Fluctuations," *American Economic Review*, 1989, *79* (1), 14–31.

_ **and Simon Gilchrist**, "The Financial Accelerator in a Quantitative Business Cycle Framework," in J.B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1 of *Handbooks in Economics*, Elsevier, 1999, chapter 21, pp. 1341–1393.

Bernstein, Shai, "Does Going Public Affect Innovation?," *Journal of Finance*, 2015, *70* (4), 1365–1403.

_ **, Xavier Giroud, and Richard Townsend**, "The Impact of Venture Capital Monitoring," *Journal of Finance*, 2016, *71* (4), 1591–1622.

_ **,** _ **, and** _ , "The Impact of Venture Capital Monitoring," *Journal of Finance*, 2016, *71* (4), 1591–1622.

Bloom, Nicholas, "The Impact of Uncertainty Shocks," *Econometrica*, 2009, *77* (3), 623–685.

_ **, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry**, "Really Uncertain Business Cycles," *Econometrica*, 2018, *86* (3), 1031–1065.

Brown, David and John Earle, "Finance and Growth at the Firm Level: Evidence from SBA Loans," *Journal of Finance*, 2017, *72* (3), 1039–1080.

Brunnermeier, Markus K. and Yuliy Sannikov, "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 2014, *104* (2), 379–421.

Buera, Francisco and Benjamin Moll, "Aggregate Implications of a Credit Crunch: The Importance of Heterogeneity," *American Economic Journal: Macroeconomics*, 2015, *7* (3), 1–42.

_ **and Roberto Fattal-Jaef**, "The Dynamics of Development: Innovation and Reallocation," 2016. Working Paper.

_ **and Yongseok Shin**, "Financial Frictions and the Persistence of History: A Quantitative Explanation," *Journal of Political Economy*, 2013, *121* (2), 221–272.

Cagetti, Marco and Mariacristina De Nardi, "Entrepreneurship, Frictions, and Wealth," *Journal of Political Economy*, 2006, *114* (5), 835–870.

Caggese, Andrea, "Financing Constraints, Radical versus Incremental Innovation, and Aggregate Productivity," *AEJ: Macroeconomics*, forthcoming.

Calcagnini, Giorgio and Enrico Saltari, "Real and Financial Uncertainty and Investment Decisions," *Journal of Macroeconomics*, 2000, *22* (3), 491–514.

Calvo, Guillermo, Alejandro Izquierdo, and Ernesto Talvi, "Phoenix Miracles in Emerging Markets: Recovering without Credit from Systemic Financial Crises," 2006. NBER Working Paper No. 12101.

_ **and Ernesto Talvi**, "Sudden Stops, Financial Factors and Economic Collapse in Latin America: Learning from Argentina and Chile," 2005. NBER Working Paper No. 11153.

Celik, Murat and Xu Tian, "Corporate Governance, Managerial Compensation, and Disruptive Innovations," 2018. Working Paper.

Chari, V.V., Lawrence J. Christiano, and Patrick Kehoe, "The Gertler-Gilchrist Evidence on Small and Large Firm Sales," Mimeo, University of Minnesota 2013.

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm Level Evidence from the 2008-2009 Financial Crisis," *Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

_ **and Antonio Falato**, "The Loan Covenant Channel: How Bank Health Transmits to the Real Economy," Working Paper 23879, National Bureau of Economic Research 2017.

Choi, Joonkyu, "Entrepreneurial Risk-Taking, Young Firm Dynamics, and Aggregate Implications," 2017. Working Paper.

Clementi, Gian and Hugo Hopenhayn, "A Theory of Financing Constraints and Firm Dynamics," *Quarterly Journal of Economics*, 2006, pp. 229–265.

Cole, Rebel, "What Do We Know about the Capital Structure of Privately Held US Firms? Evidence from the Survey of Small Business Finance," *Financial Management*, 2013, pp. 777–813.

Cooley, Thomas and Vincenzo Quadrini, "Financial Markets and Firm Dynamics," *American Economic Review*, 2001, *91* (5), 1286–1310.

_ **, Ramon Marimon, and Vincenzo Quadrini**, "Aggregate Consequences of Limited Enforceability," *Journal of Political Economy*, 2004, *112* (4), 817–847.

Cooper, Russell W. and John Haltiwanger, "On the Nature of Capital Adjustment Costs," *Review of Economic Studies*, 2006, *73* (3), 611–633.

Covas, Francisco and Wouter Den Haan, "The Role of Debt and Equity Finance Over the Business Cycle," *Economic Journal*, 2012, *122*, 1262–1286.

Cox, John, Jonathan Ingersoll, and Stephen Ross, "A Theory of Term Structure of Interest Rates," *Econometrica*, 1985, *53* (2), 385–407.

Crouzet, Nicolas and Neil Mehrotra, "Small and Large Firms over the Business Cycle," 2017. Working Paper.

Custodio, Claudio, Miguel Ferreira, and Luis Laureano, "Why are US firms uisng more short-term debt?," *Journal of Financial Economics*, 2012.

Davis, Steven, John Haltiwanger, and Scott Schuh, "Small Business and Job Creation: Dissecting the Myths and Reassessing the Facts," *Small Business Economics*, 1996, *8* (4), 297–315.

_ , _ , Kyle Handley, Ron Jarmin, Josh Lerner, and Javier Miranda, "Private Equity, Jobs and Productivity," *American Economic Review*, 2014, *104* (12), 3956–3990.

_ , _ , Ron Jarmin, and Javier Miranda, "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," in Daron Acemoglu, Kenneth Rogoff, and Michael Woodford, eds., *NBER Macroeconomic Annual*, Vol. 21 of *NBER Macroeconomic Annual* 2006, chapter 2, pp. 107–180.

Diamond, Douglas, "Debt Maturity Structure and Liquidity Risk," *Quarterly Journal of Economics*, 1991, *106* (3), 709–737.

Dinlersoz, Emin, Henry Hyatt, and Hubert Janicki, "Who Works for Whom? Worker Sorting in a Model of Entrepreneurship with Heterogeneous Labor Markets," 2017. Unpublished draft, U.S. Census Bureau.

_ , Sebnem Kalemli-Ozcan, Henry Hyatt, and Veronika Penciakova, "Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness," 2018. Working Paper.

Dixit, Avinash, "Irreversible Investment with Uncertainty and Scale Economies," *Journal of Economic Dynamics and Control*, 1995, *19* (1–2), 327–350.

Eng, Li and Margaret Shackell, "The Implications of Long-Term Performance Plans and Institutional Ownership for Firm's R&D Investments," *Journal of Accounting, Auditing and Finance*, 2001, *16* (2), 117–139.

Evans, David and Boyan Jovanovic, "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *Journal of Political Economy*, 1989, *97* (4), 808–827.

Faccio, Mara, Maria-Teresa Marchica, and Roberto Mura, "Large Shareholder Diversification and Corporate Risk-Taking," *The Review of Financial Studies*, 2011, *24* (11), 3601–3641.

Fama, Eugene and Michael Jensen, "Separation of Ownership and Control," *Journal of Law and Economics*, 1983, *26*, 301–325.

Farre-Mensa, Joan and Alexander Ljungqvist, "Do Measures of Financial Constraints Measure Financial Constraints," *Review of Financial Studies*, 2016, *29* (2), 271–308.

Fernandez-Villaverde, Jesus, Pablo Guerron-Quintana, Jauan F. Rubio-Ramirez, and Martin Uribe, "Risk Matters: The Real Effects of Volatility Shocks," *American Economic Review*, 2011, *101* (6), 2530–2561.

Fort, Teresa and Shawn Klimek, "The Effects of Industry Classification Changes on US Employment Composition," 2018. Working Papers 18-28, Center for Economic Studies, U.S. Census Bureau.

Fort, Teresa C., John Haltiwanger, Ron S. Jarmin, and Javier Miranda, "How Firms Respond to Business Cycles: The eRole of Firm Age and Firm Size," *IMF Economic Review*, 2013.

Francis, Jennifer and Abbie Smith, "Agency Costs and Innovation: Some Empirical Evidence," *Journal of Accounting and Economics*, 1995, *19* (2), 383–409.

Fuentes, Olga, Simon Gilchrist, and Marc Rysman, "Irreversibility and Investment Dynamics for Chilean Manufacturing Plants: A Maximum Likelihood Approach," 2006. Working Paper.

Gabaix, Xavier, "The Granular Origins of Aggregate Fluctuations," *Econometrica*, 2011, *79* (3), 733–773.

Gambetti, Luca and Julian Messina, "Evolving Wage Cyclicality in Latin America," 2014. World Bank Working Paper.

Gertler, Mark and Simon Gilchrist, "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *Quarterly Journal of Economics*, 1994, *109* (2), 309–340.

Gilchrist, Simon, Michael Siemer, and Egon Zakrajsek, "The Real Effects of Credit Booms and Busts," Working Paper 2018.

Giroud, Xavier and Holger Mueller, "Firm Leverage, Consumer Demand, and Unemployment during the Great Recession," *Quarterly Journal of Economics*, 2017, pp. 271–316.

Gopinath, Gita, Sebnem Kalemli-Ozcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez, "Capital Allocation and Productivity in South Europe," *Quarterly Journal of Economics*, 2017, *132* (4), 1915–1967.

Graham, Stuart, Cheryl Grim, Tariqul Islam, Alan Marco, and Javier Miranda, "Businss Dynamics of Innovating Firms: Linking U.S. Patents with Administrative Data on Workers and Firms," 2015. Working Papers 15-19, Center for Economic Studies, U.S. Census Bureau.

Greenstreet, David, "Exploiting Sequential Learning to Estimate Establishment-Level Productivity Dynamics and Decision Rules," 2007. Technical Report.

Grossman, Gene and Elhanan Helpman, "Quality Ladders in the Theory of Growth," *Review of Economic Studies*, 1991, *58* (1), 43–61.

Guzman, Jorge and Scott Stern, "Nowcasting and Placecasting Entrepreneurial Quality and Performance," in "Measuring Entrepreneurial Businesses: Current Knowledge and Challenges" University of Chicago Press 2016.

Hall, Bronwyn, "The Impact of Corporate Restructuring on Industrial Research and Development," *Brokings Papers on Economic Activity*, 1990, pp. 85–136.

Haltiwanger, John, Ron Jarmin, Rob Kulick, and Javier Miranda, "High Growth Young Firms: Contributiton to Jobs, Output, and Productivity Growth," in Haltiwanger, Hurst, Miranda, and Schoar, eds., *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*, NBER/University of Chicago Press, 2017.

Hart, Oliver and John Moore, "A Theory of Debt Based on the Inalienability of Human Capital," *Quarterly Journal of Economics*, 1994, *109*, 841–879.

Hirshleifer, David and Anjan Thakor, "Managerial Conservatism, Project Choice, and Debt," *The Review of Financial Studies*, 1992, *5* (3), 437–470.

Holmes, Thomas, David Levine, and James Schmitz, "Monopoly and the Incentive to Innovate when Adoption Involves Switchover Disruptions," *American Economic Journal: Microeconomics*, 2012, *4* (3), 1–33.

Holmstrom, Bengt and Jean Tirole, "Financial Intermediation, Loanable Funds, and the Real Sector," *Quarterly Journal of Economics*, 1997, *112* (3), 663–691.

_ **and Joan Ricart I Costa**, "Managerial Incentives and Capital Management," *Quarterly Journal of Economics*, 1986, *101* (4), 835–860.

Hopenhayn, Hugo, "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 1982, *60* (5), 1127–1150.

Howitt, Peter, "Steady Endogenous Growth with Population and R&D Inputs Growing," *Journal of Political Economy*, 1999, *107* (4), 715–730.

Hsieh, Chang-Tai and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Hurst, Erik and Annamaria Lusardi, "Liquidity Constraints, Household Wealth, and Entrepreneurship," *Journal of Political Economy*, 2004, *112* (2), 319–347.

_ **and Benjamin W. Pugsley**, "What do Small Businesses Do?," *Brookings Papers on Economic Activity*, 2011, pp. 73–118.

Huynh, Kim, Teodora Paligorova, and Robert Petrunia, "Debt financing in private and public firms," *Annals of Finance*, 2018, pp. 1–23.

Jeenas, Priit, "Monetary Policy Shocks, Financial Structure, and Firm Activity: A Panel Approach," Working Paper 2018.

Jensen, Michael and William Meckling, "Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure," *Journal of Financial Economics*, 1976, *3* (4), 305–360.

Jermann, Urban and Vincenzo Quadrini, "Macroeconomic Effects of Financial Shocks," *American Economic Review*, 2012, *102* (1), 238–271.

John, Kose, Lubomir Litov, and Bernard Yeung, "Corporate Governance and Risk-Taking," *Journal of Finance*, 2008, *63* (4), 1679–1728.

Jones, Charles, "R&D-based Models of Economic Growth," *Journal of Political Economy*, 1995, *103* (4), 759–784.

Jorgenson, Dale W., "Capital Theory and Investment Behavior," *The American Economic Review, Papers and Proceedings of the 75th Annual Meetings of the AEA*, 1963, *53* (2), 247–259.

Jovanovic, Boyan, "Selection and Evolution of Industry," *Econometrica*, 1982, *50* (3), 649–670.

Kalemli-Ozcan, Sebnem, Bent Sorensen, and Vadym Volosovych, "Deep Financial Integration and Macroeconomic Volatility," *Journal of European Economic Association*, 2014, *12* (6), 1558–1585.

_ **, Luc Laeven, and David Moreno**, "Debt Overhang, Rollover Risk, and Corporate Investment: Evidence from the European Crisis," Working Paper 24555, NBER 2018.

Khan, Aubhik and Julia K. Thomas, "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 2008, *76* (2), 395–436.

_ **and Julia Thomas**, "Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity," *Journal of Political Economy*, 2013, *121* (6), 1055–1107.

Kiyotaki, Nobuhiro and John Moore, "Credit Cycles," *Journal of Political Economy*, 1997, *105* (2), 211–248.

Klette, Tor Jakob and Samuel Kortum, "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 2004, *112* (5), 986–1018.

Kortum, Samuel, "Research, Patenting, and Technological Change," *Econometrica*, 1997, *65* (6), 1389–1420.

_ **and Josh Lerner**, "Assessing the Contribution of Venture Capital to Innovation," *The RAND Journal of Economics*, 2000, *31* (4), 674–692.

Kudlyak, Marianna and Juan M. Sanchez, "Revisiting the Behavior of Small and Large Firms during the 2008 Financial Crisis," *Journal of Economic Dynamics and Control*, 2017, *77*, 48–69.

Lemmon, Michael, Michael Roberts, and Jaime Zender, "Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure," *Journal of Finance*, 2008, *63* (4), 1575–1608.

Lentz, Rasmus and Dale Mortensen, "An Empirical Model of Growth through Product Innovation," *Econometrica*, 2008, *76* (6), 1317–1373.

Lerner, Josh, Morten Sorensen, and Per Stromberg, "Private Equity and Long-Run Investment: The Case of Innovation," *Journal of Finance*, 2011, *66* (2), 445–477.

Levinsohn, James and Amil Petrin, "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 2003, *70* (2), 317–342.

Lian, Chen and Yueran Ma, "Anatomy of Corporate Borrowing Constraints," 2015. Working Paper.

Lichtenberg, Frank and Frank Siegel, "The Effects of Leverage Buyouts on Productivity and Related Aspects of Firm Behavioir," *Journal of Financial Economics*, 1990, *27*, 165–194.

Liu, Lili, "Entry-exit, learning, and productivity change Evidence from Chile," *Journal of Development Economics*, 1993, *42* (2), 217–242.

Lyandres, Evgeny, Maria-Teresa Marchica, Roni Michaely, and Roberto Mura, "The Effects of Owners' Portfolio Diversification on Firm Strategies: Theory and Evidence from Private and Public Firms," 2018. Johnson School Research Paper Series No. 18-2013.

McCue, Kristen, "Matching Compustat Data to the SSEL," Mimeo, Center for Economic Studies, U.S. Census Bureau 2003.

McCue, Kristin and Ron Jarmin, "Matching Compustat Data to the SSEL," 2005. CES Technical Note, U.S. Census Bureau.

Mendoza, Enrique, "Sudden Stops, Financial Crises, and Leverage," *American Economic Review*, 2010, *100* (5), 1941–1966.

Meza, Felipe and Quintin Erwan, "Factor Utilization and the Real Impact of Financial Crises," *The BE Journal of Macroeconomics*, 2007, *7* (1).

Moll, Benjamin, "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?," *American Economic Review*, 2014, *104* (10), 3186–3221.

Moscarini, Giuseppe and Fabien Postel-Vinay, "The Contribution of Large and Small Employers to Job Creation at Time of High and Low Unemployment," *American Economic Review*, 2012, *102* (6), 2509–2539.

Neumeyer, Pablo and Fabrizio Perri, "Business Cycles in Emerging Economies: the Role of Interest Rates," *Journal of Monetary Economics*, 2005, *52* (2), 345–380.

Nikolov, Boris, Lukas Schmid, and Roberto Steri, "Dynamic Corporate Liquidity," 2017. Working Paper.

Oberfield, Ezra, "Short Lived Shocks and Aggregate Productivity," 2010. Working Paper.

_ , "Productivity and Misallocation During a Crisis: Evidence from the Chilean Crisis of 1982," *Review of Economic Dynamics*, 2013, *16* (1), 100–119.

Obstfeld, Maurice, "Risk-Taking, Global Diversification, and Growth," *American Economic Review*, 1994, *84*, 1310–1329.

Ottonello, Pablo and Thomas Winberry, "Financial Heterogeneity and the Investment Channel of Monetary Policy," 2018. Working Paper.

Paligorova, Teodora, "Corporate Risk Taking and Ownership Structure," 2010. Working Paper 2010-3. Bank of Canada.

Petersen, Mitchell and Raghuram G. Rajan, "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance*, 2002, *57* (6), 2533–2570.

Petrin, Amil and Jagadeesh Sivadasan, "Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs," *Review of Economics and Statistics*, 2013, *95* (1), 286–301.

Phillips, Gordon and Giorgo Sertsios, "Financing and New Product Decisions of Private and Publicly Traded Firms," *Review of Financial Studies*, 2017, *30* (5), 1744–1789.

Pratap, Sangeeta and Carlos Urrutia, "Financial Frictions and Total Factor Productivity: Accounting for the Real Effects of Financial Crises," *Review of Economic Dynamics*, 2012, *15*, 581–593.

Quadrini, Vincenzo, "Entrepreneurship, Saving, and Social Mobility," *Review of Economic Dynamics*, 2000, *3* (1), 1–40.

Queralto, Albert, "A Model of Slow Recoveries from Financial Crises," 2018. Federal Reserve Board Working Paper.

Rajan, Raghuram and Luigi Zingales, "What Do We Know about Capital Structure? Some Evidence from International Data," *Journal of Finance*, 1995, *50* (5), 1421–1460.

Robb, Alicia and David Robinson, "The Capital Structure Decisions of New Firms," *Review of Financial Studies*, 2012, *1* (1).

Romer, Paul, "Increasing Returns and Long-run Growth," *Journal of Political Economy*, 1986, *94* (5), 1002–1037.

_ , "Endogenous Technological Change," *Journal of Political Economy*, 1990, *98* (5), S71–102.

Schliefer, Andrei and Robert W. Vishny, "Liquidation Value and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance*, 1992, *47* (4), 1343–1366.

Schoar, Antoinette, "The Divide between Subsistence and Transformational Entrepreneurship," in "Innovation and Policy and the Economy," Vol. 10 of *University of Chicago Press* 2010, pp. 57–81.

Shackelford, Brandon and Raymond Wolfe, "U.S. Companies Performed $73 Billion in R&D Outside the United States in 2013," 2011. National Center for Science and Engineering Statistics Information Brief.

Shleifer, Andrei and Robert Vishny, "Large Shareholders and Corporate Control," *Journal of Political Economy*, 1986, *94*, 461–489.

Sraer, David and David Thesmar, "Performance and Bahvior of Family Firms: Evidence from the French Stock Market," *Journal of the European Economic Association*, 2007, *5* (4), 709–751.

Stella, Andrea, "Firm Dynamics and the Origins of Aggregate Fluctuations," *Journal of Economic Dynamics and Control*, 2015, *55*, 71–88.

Thesmar, David and Mathias Thoenig, "Contrasting Trends in Firm Volatility," *AEJ: Macroeconomics*, 2011, *3* (4), 143–180.

Tian, Xuan and Tracy Yue Wang, "The Tolerance of Failure and Corporate Innovation," *Review of Financial Studies*, 2014, *27* (1), 211–255.

Uribe, Martin and Vivian Yue, "Country spreads and emerging countries: Who drives whom?," *Journal of International Economics*, 2006, *69* (1), 6–36.

Vereshchagina, Galina and Hugo A. Hopenhayn, "Risk Taking by Entrepreneurs," *American Economic Review*, 2009, *99* (5), 1808–1830.

Vergara, Sebastian, "The Dynamics of Employment in Chilean Industry," 2005. Cepal Review, 86.

Virgiliu, Midrigan and Daniel Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 2014, *104* (2), 422–458.

Whited, Toni and Guojun Wu, "Financial Constraints Risk," *Review of Financial Studies*, 2006, *19* (2), 531–559.

Wooldridge, Jeffrey M., "On estimating firm-level production functions using proxy variables to control for unobservables," *Economics Letters*, 2009, *104* (3), 112–114.

Wright, Peter, Stephen Ferris, Atulya Sarin, and Vidya Awasthi, "Impact of Corporate Insider, Blockholder, and Institutional Equity Ownership on Firm Risk Taking," *The Academy of Management Journal*, 1996, *39* (2), 441–463.

Yeh, Chen, "Are firm-level idiosyncratic shocks important for U.S. aggregate volatility," 2017. Working Papers 17-23, Center for Economic Studies, U.S. Census Bureau.

Zeltin-Jones, Ariel and Ali Shourideh, "External Financing and the Role of Financial Frictions over the Business Cycle: Measurement and Theory," 2016. Working Paper.