Essays on Structural Models in Corporate Finance

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Abstract

This thesis contains two essays in Structural Corporate Finance. The first essay studies the effect of asset redeployability on the cross-section of firms' financial leverage and credit spreads. Particularly, I show that in the data firms' ability to sell assets —captured by a novel measure of asset redeployability —correlates positively with financial leverage, and negatively with credit spreads. At odds with traditional notions of asset redeployability, I show that these predictions remain even after controlling for proxies of creditors' recovery rates. To understand these empirical findings, I build a quantitative model where firms' asset redeployability decreases the degree of investment irreversibility and deadweight cost of bankruptcy. According to the model, while higher overall asset redeployability predicts larger financial leverage and lower credit spread; these relations are mainly driven by differences in the degree of investment irreversibility across firms. Also, within the model, differences in recovery rates are mainly explained by differences in deadweight costs of bankruptcy. Based on these results, I conclude that the link between firms' asset redeployability and disinvestment flexibilities is key to understand the empirical ability of asset redeployability to predict financial leverage and credit spreads.

The second essay provides new evidence about the cross-sectional distribution of debt issuance: its dispersion is highly procyclical. Furthermore, I show that this dynamic feature is mainly driven by large adjustments of the stock of debt and capital observed in good times. Previous research has highlighted the role of non-convex rigidities on inducing large adjustments on firms decisions. Then, to quantify the contribution of real and financial non-convex frictions on shaping the dynamic of the debt issuance cross-sectional distribution, I build a quantitative model where firms take investment and financing decisions. According to the model, both real and financial non-convex frictions are required to reproduce the dynamic of the cross-sectional dispersion of debt issuance. Indeed, the presence of these frictions makes firms' decisions less responsive during recessions. Yet, in booms, both non-convex costs induce large adjustment on the capital and debt stock of high-growth firms.

Lay Summary

This thesis contains two essays in Structural Corporate Finance. The first essay shows that an asset redeployability measure —capturing firms' ability to sell assets —predicts higher leverage and lower credit spreads. At odds with traditional notions of asset redeployability, these predictions remain after controlling for proxies of recovery rates. A model where asset redeployability reduces disinvestment and bankruptcy costs shows that while disinvestment costs affect significantly leverage and credit spreads, they exhibit offsetting effects on recovery rates. These results are used to explain motivating empirical findings.

The second essay provides new evidence about the cross-sectional debt issuance distribution: its dispersion is highly procyclical. I show empirically that major investment and debt issuance adjustments observed during booms can explain this procyclical behavior. I rationalize these findings through a quantitative model that highlights real and financial non-convex rigidities as necessary ingredients for rendering the cross-sectional debt issuance dispersion procyclical.

Preface

The research project in chapter 2 was identified and performed solely by the author. The essay in chapter 3 is based on unpublished research with Howard Kung (London Business School) and Hyunseob Kim (Cornell University). In this co-authored project, all authors worked on all aspects of the paper. While hard to quantify exactly, my personal share of contribution to chapter 3 amounts to about one third.

Table of Contents

List of Tables

List of Figures

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Chapter 1

Introduction

Understanding the dynamic of firms' investment and financing decisions is relevant for investors and policymakers. While firms' investment is a key component of aggregate activity; the firms' financing behavior conveys information regarding the economy's exposure to aggregate cyclical fluctuations. Accounting for their importance, the finance literature has devoted increasing attention to studying the economic mechanisms that affect these decisions at the micro-level. The general consensus is that frictions associated to capital adjustment and external financing costs are necessary to explain most of the time-series properties of the cross-sectional distribution of investment and financing decisions. Indeed, frictionless models fail dramatically even in the restricted analysis of aggregate moments.

The implications of capital adjustment costs have been extensively studied by the literature on investment. Although there has not been clear agreement about the degree of the cost associated to additions to an individual firm's capital stock, the common view is that disinvestment carries a significant cost. Indeed, in reality, firms face installation costs of new capital and/or costs of removing used capital that will be not possible to recover entirely. More broadly, firms use specialized capital that may be difficult to redeploy and therefore difficult to sell given its low liquidation value.

In this regards, in the first essay of this thesis, I examine the effects of asset redeployability on the cross-section of financial leverage (debt-to-asset ratio) and credit spreads. In the data, a measure of asset redeployability correlates positively with financial leverage and negatively with credit spreads. Furthermore, the asset redeployability measure used contains information about financial leverage and credit spreads that goes over and above expected recovery rates. Then, using a quantitative model, I assess the effect on financial leverage and credit spreads of two components of asset redeployability affecting the riskiness of a firm simultaneously. That is, a component related to disinvestment costs and a second component associated to bankruptcy costs incurred upon corporate default. To accomplish this goal, I add varying degrees of investment irreversibility and deadweight costs to a standard production-based asset-pricing model featuring firms that make optimal production, financing and default decisions. As a main result of this chapter, I highlight the link between a firm's asset redeployability and the degree of investment irreversibility that the firm faces as a key mechanism to explain the ability of asset redeployability to predict financial leverage and credit spreads in the data.

Nevertheless, in reality, firms maneuver adverse economic conditions not only by reducing unproductive capital. Indeed, firms also use external financing to keep the operating company solvent. Experience from past financial crisis suggests the presence of important frictions on raising external financing; given the severity and persistence of the economic contractions suffered on those periods. Effectively, influential works have not only confirmed the existence of financing frictions but also quantified their aggregate effects. As a consequence, operating firms have to balance capital adjustment and financial costs in order to maximize their value over time. Recently, this interaction has been proven to be key to explain the wide heterogeneity observed in debt issuances at the firm-level. In the data, on average, few firms experience large and infrequent adjustments of their stock of debt; whereas the majority of firms show small adjustments on their debt stock from quarter to quarter. Although the literature on corporate finance has studied the importance of financing friction on the time-series properties of the aggregate debt issuance; little is known about their role on inducing business cycle dynamics on the entire firm-level distribution. Studying the dynamics of entire firm-level distribution of debt issuance is crucial as it can guide our understanding about the wide range of responses exhibited by firms in terms of their use of debt over the business cycle. As a response to this concern, in the second essay of this thesis I contribute to this research area.

In the second essay, I start documenting that the cross-sectional dispersion of debt issuance is significantly procyclical. Next, I show evidence that suggests that periods of both positive debt-issuance and investment lumpiness are responsible of this procyclical pattern exhibited by the debt issuance cross-sectional dispersion. Then, to further investigate the economic determinants of this behavior, I construct a structural general equilibrium model of heterogeneous firms featuring both lumpy investment and debt financing decisions. The model shows that neither non-convex cost of investment nor non-convex cost of issuing debt alone can reproduce the empirical behavior of the debt issuance distribution. In fact, I show that the model needs a careful calibration of both types of frictions to account for the motivating empirical results.

Finally, because each essay intends to answer a different research question, chapters are designed to be self-contained. Indeed, I provide a detailed discussion of the research question and contribution of each essay in the introductory section specific to each chapter.

Chapter 2

Asset Redeployability, Capital Structure and Credit Spreads

2.1 Introduction

A seminal idea in economics is that assets which are redeployable - that is, have alternative uses - also have high liquidation values.[1] While assets with high liquidation values can be sold at prices that are close to their value in best use, firms selling assets with low liquidation values can experience significant discounts. Early literature on corporate finance has claimed that costly liquidation of assets is an important determinant of the partial irreversibility of investment faced by an operating firm (Abel and Eberly (1995)). This link arises since costly liquidation of assets drives a wedge between the purchase and selling price of a firm's capital stock.[2] Furthermore, costly liquidation of assets has also been identified as a source of the indirect deadweight costs incurred upon corporate defaults (Acharya et al. (2007)). Indeed, indirect deadweight costs can be substantial in the case the shocks that cause a firm's default also have the potential to force it to liquidate assets at abnormal discounts.[3] Recently, a growing literature on corporate finance has used different proxies of firms' asset redeployability to examine its positive effect on the terms for debt. Yet, to the extent that low asset redeployability increases real frictions faced by a firm at several stages of its life, existing studies are silent about the relative effect of these frictions on the firms' capital structure decisions. The goal of this chapter is to examine whether firms' capital structure and credit spreads are affected by asset redeployability purely through the investment-irreversibility channel and/or through the deadweight-cost channel. I

[1] Riordan and Williamson (1985), and Williamson (1988) represent early papers articulating this relation.

[2] Bertola (1988) and Abel and Eberly (1995, 1996) study firms' investment in the presence of asymmetric capital adjustment costs. Barnett and Sakellaris (1998) presents empirical evidence that supports these theories.

[3] Shleifer and Vishny (1992) proposes a theory of fire sales where assets' selling prices of a distressed firm depend on its peers financial condition. Pfunder (2008) argues that even if a firm's peers could raise funds, antitrust regulations can prevent them from purchasing the liquidated assets. In the data, Schuermann (2004) show that recovery rates are 19% and 15% points lower in recessions and in periods of industrial distress, respectively.

do so by studying comprehensively the determinants of firms' leverage and credit spreads in the data and through the lens of a quantitative model.

This chapter makes three contributions. First, I complement existing studies linking firms' asset liquidity to capital structure outcomes, by showing that a novel measure of asset redeployability proposed by Kim and Kung (2016) is able to predict not only leverage ratios but also credit spreads. Second, I show that the information captured by the asset redeployability measure that is not explained by expected recovery rates also predicts leverage ratios and credit spreads. Specifically, in the data, I show that both expected recovery rates as well as the component of the asset redeployability measure that is not explained by expected recovery rates contribute to predict leverage ratios and credit spreads.[4] Motivated by this result and previous literature linking creditors' recovery rates to indirect deadweight costs caused by costly liquidation of assets (Acharya et al. (2007)), the last contribution of this chapter is to quantify the relative importance of both the investment-irreversibility and the deadweight-cost channels to determine leverage ratios decisions and credit spreads. I do so by adding varying degrees of deadweight costs and investment irreversibility to a standard production-based asset-pricing model in order to assess the contribution on leverage ratios and credit spreads of these two dimensions.

In line with the notion that indirect deadweight costs affect negatively creditors' recovery values at default (Acharya et al. (2007)), I find that a high level of deadweight costs implies higher credit spreads in the data and in the model. Intuitively, since shareholders declare bankruptcy when the levered equity value becomes negative, which is more likely to happen in recessions when the price of risk is high, assets associated to high deadweight costs will be less desirable to firms' investors. Bondholders will anticipate higher costs upon default translating them to lower debt prices. Consequently, asset redeployability will decrease equilibrium credit spreads through the deadweight-cost channel. Importantly, I find in the data and in the model that the increase in credit spreads caused by the deadweight-cost channel does not lead to lower firms' leverage ratios. Within the model, firms' investment decisions do not change significantly when deadweight costs increase. Then, in the presence of more expensive debt, firms facing higher deadweight costs increase debt issuances to continue covering their financial needs. Lastly, despite the direction of the effect of the deadweight-cost channel on credit spreads being clear, its magnitude is less obvious. Within the model, I show that the importance of this channel on credit spreads depend on the degree of the investment irreversibility. In particular, the deadweight-cost channel becomes relevant for firms facing significant real frictions.

Within the model, the low levels of investment irreversibility will have two reinforcing effects on credit spreads. First, since increasing investment irreversibility increases the value of the option of delaying investment, the firms' unlevered value upon default will tend to be lower. Second, in the presence of fixed operating costs in the production function of the firm, larger disinvestment adjustment costs will make it harder for firms to deploy their excess capital when the economy experiences

[4]Expected recovery rates are built by implementing a KMV-like model in the data (Bohn and Crosbie (2003)). Section 2.6 provides more descriptions of the KMV model implemented. Appendix A shows technical details.

bad shocks, which will end up increasing the aggregate probability of default. Within the model, bondholders anticipate the reduction of the *expected* value of their claims by decreasing debt prices and therefore increasing credit spreads. Regarding the effect of the investment-irreversible channel on leverage ratio, note that the lower value of investment options will impact negatively firms' financial needs which will allow them to decrease their debt issuance and therefore their leverage ratios. Overall, the effect of low asset redeployability throughout the investment irreversibility channel will have a positive effect on credit spreads and a negative effect on leverage. I expect these effects to be non-linear.

To assess the quantitative importance of these two channels affected by asset redeployability, I calibrate the quantitative model to match a broad set of aggregate moments and moments associated to portfolios formed based on the asset redeployability dimensions. In the model, differences along indirect deadweight costs, partial irreversibility of investment and idiosyncratic technology shocks are the only differences across firms. The degree of cross sectional heterogeneity in indirect deadweight cost is set to match the cross sectional dispersions of recovery rates reported by Altman et al. (2004). Similarly, the degree of cross sectional heterogeneity in partial irreversibility of investment is chosen to match the cross sectional difference in excess return exhibited in the data by firms in the lowest and highest asset redeployability quintile.

In line with recent empirical studies, I find that both the deadweight - cost and investment - irreversibility channels increase credit spreads. The benchmark calibration produces a large difference in credit spreads between the low- and high-asset redeployability portfolios, about 46bps. This prediction of the model is validated in the data using a panel of publicly corporate bond transactions. In the data, firms with low levels of asset redeployability pay about 20bps more on their debt. These results are statistically significant and are robust to various controls. Notably, in economic terms, this difference in credit spreads represents $0.8 millions of additional annual interest payments for firms with less redeployable assets.[5] In the model, as in the data, the higher cost of debt leads firms with low redeployable assets to use less financial (book) leverage. The difference in book leverage between the high- and low-asset redeployability quintile is 5.6%. This last result accords with Kim and Kung (2016) who reports that average book leverage increases in firms' ability to redeploy their assets. In short, the model's prediction that the degree of asset redeployability leads firms to use more and less expensive debt is supported in the data, both qualitatively and quantitatively.

The dynamic model also allows us to quantitatively assess to what extent asset redeployability affects credit spreads and leverage purely through the investment-irreversibility channel and/or through the deadweight-cost channel. By performing multiple simulations and averaging firms within different combinations of deadweight cost and degree of investment irreversibility, I compute the average elasticity of credit spreads with respect to changes in the degree of investment irreversibility and deadweight cost. On average, the elasticity of credit spreads with respect to changes in investment

[5]These values are obtained assuming a debt face value of $392 millions (the average face value in the sample).

irreversibility is about twice as large as the elasticity of credit spreads with respect to changes in deadweight cost. Particularly, a 1% decrease in deadweight cost implies a 0.17% increases in average credit spreads. The larger effect of investment irreversibility is explained by two reinforcing effects. First, for a given deadweight cost, a firm facing a higher degree of investment irreversibility will optimally reduce its investment which leads to a lower capital stock in equilibrium. The lower capital stock occurs at the same time the firm faces low flexibility to restructure its assets, which will affect the claim of firm's creditors upon a likely default. Indeed, in the presence of operating costs, higher degree of investment irreversibility will impact firms' ability to adapt operations in response to poor economic conditions.

It is worth mentioning that although the investment-irreversibility channel seems to play a more important role than the deadweight-cost channel in determining credit spreads, the effects of these two dimensions are not enough quantitatively to explain the empirical average credit spreads in a model that only considers one-period debt. The average credit spreads in the data is about 90bps whereas the one-period debt version of the model can only generate an average credit spreads of 53bps. This drawback of short-term debt has been pointed out in the recent literature (e.g. Michaux and Gourio (2012)). Intuitively, when only short-term debt is considered, firms can easily change their total leverage which lowers default probabilities and leads to low credit spreads in equilibrium.

Furthermore, long-term debt plays a role generating the difference in credit spreads exhibited by low- and high-asset redeployability firms. A version of the model that only considers one-period debt only generates a difference of 12bps between credit spreads exhibited by firms with low and high redeployable assets; which is significantly lower to the same difference generated by the benchmark model (46bps). To understand the intuition of the results, it is useful to compare the choice of debt maturity structure of firms with high redeployable assets versus the one chosen by firms with low asset redeployability. Relative to the one-period debt model, in the benchmark model both high- and low-asset redeployability firms increase their debt maturity structure on average. Yet, firms with less redeployable assets tend to keep a longer debt maturity structure than firms with high redeployable assets. This occurs because these firms face large financial needs in bad times due to the presence of operating cost and the impossibility of scaling down their unproductive capital. Within the model, the term structure of credit spreads is upward sloping in bad times; making long-term debt more expensive than short-term debt. Ultimately, firms with less redeployable assets end up combining costly equity issuances and debt issuance at high credit spreads in order to fund their financial needs. In contrast, firms with highly redeployable assets pay their financial needs in bad times mainly using short-term debt which is cheaper than long-term debt in recessions. These optimal debt maturity strategies lead to a more procyclical debt maturity structure of firms with high redeployable assets relative to the one exhibited by firms with low redeployable assets. Particularly, in the data, the correlation between the output growth and the average maturity exhibited by firms in the highest asset redeployability quintile is 0.25 higher than the correlation between the output growth and the average maturity exhibited by firms in the lowest asset redeployability quintile. The model is able to generate similar results.

2.1.1 Literature review

This chapter contributes to the literature which studies the effect of a firm's ability to redeploy and sell its assets on determining its risk and capital structure outcomes.

Early works by Riordan and Williamson (1985) and Williamson (1988) argue that a firm's asset redeployability is an important determinant of liquidation value of the firm's assets. Theoretical works by Hart and Moore (1991), Shleifer and Vishny (1992), and Holmstrom and Tirole (1997), have suggested that high liquidation value of assets allows managers to alleviate firms' financial constraints. Intuitively, these works claim that high liquidation values allow firms to reduce indirect deadweight costs of corporate bankruptcy which increases the amount recovered by firm's creditors upon default. In contrast, Myers and Rajan (1995), Weiss and Wruck (1998) and Morellec (2001) reach opposite conclusions by arguing that lower asset liquidity makes it more costly for distressed managers to expropriate value from bondholders and thus, under this notion high asset redeployability does not alleviate firms' financial constraints. Kim and Kung (2016) show empirically that low asset redeployability, by decreasing liquidation values of assets, is also an important source of investment irreversibility that can impair firms' operating flexibility over their entire life and particularly during economic downturn. In fact, Mauer and Triantis (1994) and Aivazian and Berkowitz (1998) use a theoretical framework to show that real flexibilities create value by lowering firms' default risk and increasing their debt capacity. My work intends to fill a gap in this literature by analyzing to what extent corporate decisions as well as credit spreads can be explained by asset redeployability through two distinct channels, namely the investment-irreversibility and the deadweight-cost channels.

Based on measures that capture creditors' recovery upon default, recent empirical work finds a positive link between assets' liquidation values and a wide set of capital structure outcomes. Benmelech (2008), using a novel data set of nineteenth-century American railroads, shows that high liquidation values of assets allow firms to increase the debt maturity as well as the amount of debt issued.[6] Benmelech and Bergman (2009) finds that debt tranches of airlines secured with more redeployable collateral exhibit lower credit spreads. Using a broader sample of industries, Ortiz-Molina and Phillips (2010) also find that firms in industries with more liquid assets, and during periods of high asset liquidity, face a lower cost of capital.[7] Campello and Hackbarth (2012) uses a theoretical model to show a positive effect of liquidation value at default on corporate financing, among financially constrained firms. Recent literature studies to what extent a firm's ability to adjust assets enhances its operating and financial flexibility. Schlingemann et al. (2002), using Compustat Full-Coverage Industry Segment File (CISF) database, examines how asset liquidity can explain firms' internal restructuring process; which, as showed by Almeida et al. (2011), is especially valuable to firms facing economic hardship.

[6] In a related paper, Liu and Liu (2011) use real estate firms, i.e. the real estate investment trusts (REITs), to examine how asset liquidation values influences a firm's debt capacity.

[7] Campello and Giambona (2013) validates these results using Compustat-based measure that entails breaking down tangible assets into their identifiable parts, which include land and buildings, machinery and equipment.

In the asset pricing literature, Kogan (2004), Gomes et al. (2003a), Carlson et al. (2004), Zhang (2005) and Cooper (2006) argue that since firms facing difficulties in scaling down their unproductive capital due to adjustment costs will be unable to cut fixed costs in economic downturn, they will offer less protection against aggregate negative shocks and therefore their investors will require higher returns in exchange of capital.[8] Gala (2010) provides a general equilibrium argument to explain why investors require a higher return for investing in firms facing important real frictions to (dis)investment. More broadly, this chapter relates to the growing production-based asset-pricing literature that studies firms' optimal real and financial decisions in the context of multiple market frictions to explain the relationship between corporate decisions and asset prices. In economic terms, firms become safer as they are able to respond to negative shocks by using efficiently both their operational and financial flexibilities. Bloom (2009) and Belo et al. (2014) are recent papers that belong to the investment and labor demand literature that investigates the importance of capital and labor adjustment costs in explaining corporate decisions' dynamics. Gomes (2001), Hennessy and Whited (2005, 2007), Carlson et al. (2006), and Belo et al. (2016) are a subsample of papers that examine the impact of financial frictions on corporate investment and asset prices. Among these papers, firms' inability to adapt operations and/or substitute between different marginal sources of financing (internal or external) during bad economic times plays an important role in determining firms' risk premiums at the equilibrium. I contribute to this literature by studying capital structure's implications of disinvestment and bankruptcy deadweight costs affecting firms' ability to liquidate their assets over the business cycle. Interestingly, I find that the degree of the disinvestment rigidity amplifies the effect of deadweight costs on firms' credit spreads.

By studying the effect of debt maturity decisions on credit spreads, this chapter also relates to a growing strand of literature studying debt maturity decisions. In terms of theoretical research, a widely used framework for debt maturity structure is based on Leland (1994, 1998) and Leland and Toft (1996) who, for the sake of tractability, take the frequency of debt refinancing as a fixed parameter. Chen et al. (2012), and Brunnermeier (2009) develop a calibrated model to match procyclicality of aggregate debt maturity structure. Unlike recent papers studying debt maturity structure and credit spreads (e.g. Brunnermeier and Oehmke (2013) and He and Milbradt (2015)), my work incorporates dynamic investment decisions. As mentioned by Michaux and Gourio (2012), adding this layer to the model is key to match credit spreads.

Credit spreads and debt maturity decisions has also been studied in the context of models with asymmetric information (e.g. Flannery (1986), and Diamond (1991)). These models price debt contracts assuming the existence of a pooling equilibrium. In contrast to this class of models, the model proposed in this chapter features complete information and produces equilibrium where firms with highly redeployable assets use their operating flexibility and low (indirect) deadweight costs to issue the cheapest type of debt leading to low credit spreads and high leverage. In contrast, in models with

[8]In constrast, Ozdagli (2012) proposes a model without operating leverage where partial irreversibility of investment makes firms less risky since the value of the disinvestment option provides insurance in bad times.

asymmetric information, good type firms will prefer to issue short-term debt to differentiate themselves from the bad type firms that prefer long-term debt to minimize their probability of default.

The rest of the chapter is organized as follows. Section 2.2 develops a simple two-period model where I describe how the two channels proposed in this chapter, that relate to asset redeployability, affect a firm's leverage and credit spreads. Section 2.3 extends the simple model into a quantitative model. Section 2.4 discusses the baseline calibration. Section 2.5 investigates some of the model's quantitative implications for the cross-section of capital structure and credit spreads. Section 2.6 presents several empirical tests and it is followed by a few concluding remarks in section 2.7.

2.2 A simple model

This section develops a two-period model to highlight how the two economic channels studied in this chapter that relate to asset redeployability can affect firms' leverage and credit spreads.

Economic environment I assume agents are risk neutral and the gross interest rate is set to 1. The simple model incorporates a capital adjustment cost function that is general enough to consider both symmetric-convexity and irreversibility as special cases. The firm's indirect deadweight cost at default is modeled as a proportional cost. Thus, at default, creditors take over the firm and incur a bankruptcy cost when liquidating the capital stock.

Technology A firm is in place for two periods $t \in \{1,2\}$ and faces a technology shock represented by the stochastic term X_t which is described by a lognormal random-walk process, $X_t = X_{t-1}e^{\varepsilon_t}$ with $\varepsilon_t \sim i.i.d\, N(\mu, \sigma^2)$. Technology is described by a decreasing return to scale Cobb-Douglas production function $Y(X_t, K_t) = X_t K_t^{\alpha}$ with $\alpha \in (0,1)$.

Capital adjustment cost $\Phi(K_t, I_t)$ denotes the cost of changing the stock of capital by I_t units when the capital stock is K_t. As in Zhang (2005), the functions $\Phi(K_t, I_t)$ writes,[9]

$$\Phi(K_t, I_t) = K_t \left(\frac{I_t}{K_t} - \delta\right)^2 \left[\mathbb{I}_{\{I_t \geq 0\}}\theta_1 + \mathbb{I}_{\{I_t < 0\}}\theta_2\right] = \phi(K_t, I_t)\left[\mathbb{I}_{\{I_t \geq 0\}}\theta_1 + \mathbb{I}_{\{I_t < 0\}}\theta_2\right] \tag{2.1}$$

where $\theta_1, \theta_2 > 0$ and $\mathbb{I}_{\{x\}}$ represents an indicator function that takes value 1 if x is true and zero otherwise. The partial-irreversible-investment case corresponds to $\theta_1 < \theta_2$.

Deadweight cost of bankruptcy It is denoted by $\chi \in [0,1]$, where χ is a proportional bankruptcy cost —proportional to creditors' recovery at default, i.e. the unlevered firm value —that creditors incur when the firm's capital stock is liquidated upon default.

Timeline In period 1 the firm starts with a capital stock K_1 and decides its investment I after observing the technology shock X_1. Investment allows the firm to change its capital stock to $K_2 =$

[9] This expression is similar to the one used in the benchmark model. This functional form guarantees that it becomes zero at the steady state of the dynamic problem. As discussed by Cooper and Haltiwanger (2006) this functional form also guarantees that, in the firm's problem, the (expected) marginal productivity of capital depends on investment rate values.

$K_1(1-\delta)+I$ at period 2. Due to the presence of equity issuance costs, $\Psi(\cdot)$, the firm also finances I by issuing one-period debt which is priced by competitive creditors. To decide the amount of debt issued, i.e. face value B, the firm balances equity issuance and bankruptcy costs. In period 2, after observing the shock X_2, shareholders decide whether or not to declare bankruptcy. If default does not occur, the firm pays the promised debt B, liquidates its assets and distributes all residual claim as dividend. Importantly, if the firm declares bankruptcy, creditors take over the unlevered firm incurring the additional bankruptcy cost χ.

Firm's value At period 2, the firm's value conditional on the initial capital stock K_2 and technology shock X_2 writes as a call option granted by creditors to shareholders on the company's operating assets with a strike price that is equal to the debt face value. Shareholders will continue operating the firm as long as its operating assets are enough to honor debt payments,

$$\begin{aligned} V_2(X_2,B) &= \max\Big\{0\,,\,\Pi(X_2,K_2)+L(K_2)-B\Big\} \\ \text{subject to: } \quad \Pi(X_2,K_2) &\equiv Y(X_2,K_2)-f_0 \\ L(K_2) \quad &\equiv K_2-\phi(K_2,-K_2)\theta_2 = K_2(1-\theta_2) \end{aligned} \tag{2.2}$$

where V_2 represents the firm's value at period 2, and f_0 denotes a fixed cost that is necessary to pay in order to operate the firm's assets. The value of the option of equity considers the benefit shareholders can obtain from selling the firm's assets at the end of period 2, i.e. $L(K_2)$. When liquidating its assets, the firm incurs the cost $\phi(K_2,-K_2)\theta_2 = K_2\theta_2$. Default occurs if the shock at period 2 is below the threshold $X_2^\star(K_2,B)$ that makes V_2 equal to zero. Formally,

$$\Pi(X_2^\star(K_2,B),K_2)+L(K_2)-B=0 \tag{2.3}$$

From equation (2.3), an increase of the investment irreversibility (high θ_2) does not only affect the liquidation value of the capital stock K_2 but it also reduces the firm's value. This, since the firm will optimally decrease investment at period 1 due to a lower expected marginal productivity of capital. Note that because of the lower financial needs at period 1, the firm will also reduce the amount of debt issued at this period. The final effect of an increase of θ_2 on the probability of default will depend on the relative change of K_2 and B, that is the firm's leverage ratio. The effect of θ_2 on credit spreads will be a function of the change in the expected default probability and expected recovery rates (defined below). If the firm decides to default, i.e. $X_2 < X_2^\star(K_2,B)$, bondholders will take over the unlevered firm and keep operating it for values of the technology shock X_2 larger than the threshold $X_2^\star(K_2,0)$, which satisfies $\Pi(X_2^\star(K_2,0),K_2)+L(K_2)=\chi K_2$. An increase of χ will decrease liquidation value of the firm's assets as an increase of θ_2 will do. Yet, an increase in θ_2 will have stronger effects due to its large negative link with investment. In period 1, after observing X_1 and the capital stock K_1, the firm's problem reduces to,

$$V_1(X_1,K_1) = \max\Big\{0, \max_{I,B}\Big\{D(X_1,K_1,I,B) + \mathbb{E}\Big(V_2(X_2,K_2,B)\mathbb{I}_{\{X_2>X_2^\star(K_2,B)\}}\Big)\Big\}\Big\}$$

$$\begin{aligned} \text{subject to: } \; & K_2 \equiv K_1 + I \\ & D(X_1,K_1,I,B) \equiv E(X_1,K_1,I,B) - \Psi(E(X_1,K_1,I,B)) \\ & E(X_1,K_1,I,B) \equiv \Pi(X_1,K_1) - I - \Phi(K_1,I) + P(B,K_2) \end{aligned} \tag{2.4}$$

where δ has been set to zero in the first constraint. The second constraint shows that distributions to shareholders, $D(\cdot)$, are given as equity payout $E(\cdot)$ net of equity issuance costs $\Psi(E(\cdot))$. As in the benchmark model, equity issuance costs are modeled as the sum of a fixed ψ_0, and a proportional ψ_1 component. Lastly, $P(B,K_2)$ denotes the debt price associated to the face value B and conditional on the firm's optimal decisions.

Price of debt In a competitive market, $P(B,K_2)$ equals the discounted future bond payoffs obtained when the firm is operating and in the case shareholders decide to default,

$$\begin{aligned} P(K_2,B) = \; & \mathbb{E}\Big(B \cdot \mathbb{I}_{\{X_2>X_2^\star(K_2,B)\}}\Big) \\ & + \mathbb{E}\Big((\Pi(X_2,K_2) + L(K_2) - \chi K_2)\mathbb{I}_{\{X_2^\star(K_2,0)<X_2<X_2^\star(K_2,B)\}}\Big) \end{aligned} \tag{2.5}$$

In words, the first term in equation (2.5) represents the debt payment in the case shareholders continue operating the firm, whereas the second term denotes payments at default. Finally, given the assumptions of the model, the firm's credit spreads $CS(B,K_2)$ can be written as,

$$CS(B,K_2) = \frac{B}{P(B,K_2)} - 1 = \frac{1-RR(B,K_2)}{1-PD(B,K_2)} - 1 \tag{2.6}$$

The first equality in equation (2.6) implies that adding the credit spreads to the (gross) risk free rate allows agents to recover the risky debt price by discounting the debt face value as if default never occurs. The second equality in equation (2.6) shows that the credit spreads can be written in term of the expected default probability $PD(B,K_2)$ and recovery rate $RR(B,K_2)$.[10]

Results The remainder of this section discusses the role of the degree of partial irreversibility of investment θ_2 and deadweight cost χ in determining the firm's credit spreads and leverage. At period 1, the firm balances equity issuance and bankruptcy costs to determine the optimal debt level B. Indeed, a low level of debt forces the firm to use a combination of internal earnings and costly equity issuance to finance capital expenditures. Yet, by decreasing the probability of default at period 2, a

[10] Where the expected default probability $PD \equiv PD(B,K_2)$ and recovery rate $RR \equiv RR(B,K_2)$ are defined as,

$$PD = \mathbb{E}\Big(\mathbb{I}_{\{X_2^\star(K_2,0)<X_2<X_2^\star(K_2,B)\}}\Big) \quad \text{and,} \quad RR = \frac{1}{P(B,K_2)}\mathbb{E}\Big((\Pi(X_2,K_2) + K_2(1-\chi-\theta_2))\mathbb{I}_{\{X_2^\star(K_2,0)<X_2<X_2^\star(K_2,B)\}}\Big)$$

for more details refer to Appendix B that shows how to compute $PD(\cdot)$ and $RR(\cdot)$ for the more general case.

low level of debt reduces the exposure to bankruptcy costs. To determine the relative importance of partial irreversibility of investment and deadweight cost on the firm's decisions, the model is solved for multiple values of θ_2 and χ. Next, I compute marginal effects of θ_2 and χ on different firm's decisions. In Figure 2.3, red (black) lines show the average marginal effect of increasing the degree of partial irreversibility of investment, θ_2, (deadweight cost, χ) on multiple firm's variables; keeping the deadweight cost, χ, (partial irreversibility of investment, θ_2) unchanged.

The top-left graph shows that investment, I, decreases more after an increase of investment irreversibility (high θ_2) than after increasing of deadweight cost (high χ). A decline in investment reduces the firm's financial needs which translates to a reduction of the amount of debt issued (top-center graph). Note that the reduction of debt issuance is more pronounced after an increase of investment irreversibility than after a decline in deadweight cost. Ultimately, the top-left graph shows the effect on leverage of changes in the two parameters studied.

When investment becomes more irreversible, the optimal capital stock of the firm decreases due to a lower value of the option to invest; this, at the same time, decreases significantly the firm's financial needs which leads to a lower leverage ratio. In contrast, even when the deadweight cost increases, the firm does not adjust its investment significantly and thus its financial needs continue being high. However, due to higher deadweight costs, the firm's creditors provide less funds per unit of face value. Consequently, the firm needs to increase its leverage ratio in order to be able to fund its investment.

Note that in this numerical example, changes in credit spreads only come from change in the expected recovery rate of the debt issued. Due to the discrete nature of X_t in the numerical exercise, the range of values for θ_2 and χ guarantees that the probability of default remains unaltered (bottom-left graph). It is worth mentioning that for reasonable values of the level of investment irreversibility and deadweight cost, both channels studied in this chapter that relate to asset redeployability exhibit similar effects on credit spreads but their effects on leverage ratios differ. To summarize, the simple model shows that there is a positive relationship between investment irreversibility and credit spread, and a negative one with financial leverage. On the other hand, there is a positive link between higher deadweight costs, and both credit spread, and financial leverage.

The distinct effects of the channels of asset redeployability studied highlight the importance of considering different aspects of a firm affected by its ability to redeploy its assets. Furthermore, despite that the simple model allows us to understand the main mechanisms, a rigorous quantification of the contribution of each channel must consider that in practice partial irreversibility of investment will not necessary be an important constraint for all firms; which may end up weakening the marginal effects found in this section. Indeed, the importance of partial irreversibility of investment will depend on —among other factors —the firm's current stock of capital and the degree of its financial constrains. Additionally, and as it is shown in the dynamic model, the importance of the deadweight channel will depend on how close the firm is to distress. Intuitively, when a firm is far from defaulting its creditors will not be concerned with factors affecting their recovery upon default. The next section intends to address these issues that at first are difficult to be captured by a simple two-period model.

2.3 Benchmark model

This section extends the simple model into a dynamic stochastic partial equilibrium model. It considers infinitely lived firms in discrete time. Firms issue debt and equity and are owned by risk-averse investors. I study whether the channels highlighted previously are quantitatively sufficient to explain the cross-sectional differences in the data showed by firms sorted on asset redeployability. The relative importance of each channel is assessed based on its contribution to leverage and credit spreads.

2.3.1 Firms

The core of the model consists of a stochastic discount factor and a cross-section of heterogenous firms that make optimal investment and financing decisions by balancing real and financing costs. The stochastic discount factor is derived from a representative household who has recursive preferences and an exogenous consumption process as in Kuehn and Schmid (2014).

At period t, the firm's chooses its new factor demand, k_{t+1} and how to finance these purchases in order to maximize the present value of shareholders' after-tax cashflows. To finance its capital demand and distributions, the firm can use either internal earnings available at the beginning of the period or new debt issues. If the funding raised through these two sources is not enough, the firm can also choose to issue new costly equity. Regarding debt contracts, firms issue a combination of short- and long-term debt.[11] Specifically, at each period t the firm can control the total face value of debt outstanding b_{t+1} and the speed at which its debt matures over time by adjusting its *average maturity*. The firm's average maturity of its bonds is determined by the variable $\lambda_{t+1} \in [0,1]$ which implies that at time $t+1$ only a fraction λ_{t+1} of the total face-value of the debt outstanding b_{t+1} is paid back to bondholders.[12] In addition to the fraction of principal repaid, borrowers pay a coupon per period that corresponds to a proportion of the total debt face value determined by a fixed coupon rate $c \in (0,1)$.

Production Technology

At period t, output is given by the production function $y_t = y(k_t, x_t, z_t)$; where x_t denotes a persistent aggregate productivity shock which follows a random walk with time-varying drift and volatility; and z_t denotes an idiosyncratic shock affecting the firm's cash flows through its operating leverage which follows a mean-reverting process. Particularly, x_t and z_t follow,

$$\ln(x_{t+1}/x_t) = g + \mu_x(s_t) + \sigma_x(s_t)\varepsilon_t^x \tag{2.7}$$

$$\ln(z_t) = (1-\rho_z)\bar{z} + \rho_z \ln(z_{t-1}) + \sigma_z \varepsilon_t^z \tag{2.8}$$

where ε_t^x and $\varepsilon_t^z \sim i.i.d\, N(0,1)$. The low-frequency component in the aggregate productivity equation, $\mu_x(s_t)$ is used to generate sizeable risk premia as in Bansal and Yaron (2004) whereas the time-varying

[11] Following a similar framework as in Brunnermeier (2009), Michaux and Gourio (2012), Chen et al. (2012), Brunnermeier and Oehmke (2013) and He and Milbradt (2015).

[12] Ignoring the coupon, the average debt maturity is computed as, $\lambda_{t+1} \sum_{j=1}^{\infty} j \times (1-\lambda_{t+1})^{j-1} = 1/\lambda_{t+1}$.

volatility is useful to generate realistic credit spreads. Each firm produces according to the decreasing return to scale Cobb-Douglas production function,

$$y(k_t, x_t, z_t) \; = x_t^{1-\alpha} k_t^{\alpha} - f z_t - \phi k_t \tag{2.9}$$

where f and ϕ represent a fixed and a proportional cost, respectively. In the calibration, ϕ is set to match the average book-to-market ratio and f is used to calibrate default rates.[13]

Investment

Firms are allowed to scale operations by choosing the level of capital k_{t+1} which is accomplished through investment, i_t. Firms' capital accumulation is such that, $i_t \equiv k_{t+1} - (1-\delta)k_t$, where the depreciation rate of capital is denoted by $\delta \in (0,1)$. I model real options by assuming that firms face a cost of adjusting capital $\Phi(k_t, i_t, \omega_t)$ where the stochastic variable ω_t controls one of the dimensions of asset redeployability studied, i.e. the investment-irreversibility channel, described in Section 2.4.

Equity value

Shareholders have the right to firms' dividends as long as they are operating. Distributions to shareholders, d_t are given by equity payout e_t net of issuance costs $\Psi(\cdot)$. Equity payouts are equal to firms' free cash-flow; that is, the operating profit, net of cash flows from financing and investment activities,

$$\begin{aligned} e(k_t, b_t, \lambda_t, \Gamma_t) \; &= (1-\tau) y(k_t, x_t, z_t) - i_t - \Phi(k_t, i_t, \omega_t) - (\lambda_t + c(1-\tau))\, b_t + \tau \delta k_t \\ &\quad + P(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_t)\,(b_{t+1} - (1-\lambda_t) b_t) \end{aligned} \tag{2.10}$$

where τ denotes the effective tax rate and Γ_t summarizes the vector of aggregate and idiosyncratic stochastic variables $(x_t, z_t, \omega_t, \chi_t)$, where χ_t is the stochastic variable related to the deadweight-cost channel (described in Section 2.3.1). The first term captures the firm's operating profit, from which the required investment expenses, $i_t + \Phi(k_t, i_t, \omega_t)$, and debt repayments, $(\lambda_t + c(1-\tau))\, b_t$ are deducted. Note that capital depreciation and debt interest payment generate tax shields. The debt price function $P(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_t)$ will be a function of stochastic variables Γ_t and optimal decisions at time t. It follows that the value of the firm to its shareholders, denoted $J(\cdot)$, is the present value of distributions $d_t \equiv e_t - \Psi(e_t)$ plus the expected firm's continuation value. Following Gomes et al. (2014), it writes,

$$J(k_t, b_t, \lambda_t, \Gamma_t) = \max \Big\{ 0, \max_{k_{t+1}, b_{t+1}, \lambda_{t+1}} \Big\{ d_t + \mathbb{E}_t (M_{t,t+1} J(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_{t+1})) \Big\} \Big\} \tag{2.11}$$

where $M_{t,t+1}$ is the equilibrium stochastic discount factor derived from the representative household's preferences (described in Section 2.3.2). The first *max* operator captures the limited liability of shareholders. The second *max* operator relates to the determination of optimal decisions of firms' manager.

[13] Since the economy is persistently growing, $g > 0$, in the solution of the model the fixed cost f is multiplied by aggregate technology shock x_t to keep it economically sizable along the balance growth path of the firm.

Default

Several observations about the value of equity will be useful later. First, limited liability implies that equity value, $J(\cdot)$, is bounded and will never fall below zero. This implies that equity holders will default on their credit obligations whenever their idiosyncratic shock z_t is above a cutoff level $z^\star(k_t, b_t, \lambda_t, x_t, \omega_t, \chi_t)$ determined by the threshold default condition,

$$J(k_t, b_t, \lambda_t, \Gamma_t^\star) = 0 \quad \text{with,} \quad \Gamma_t^\star \equiv (x_t, z^\star(k_t, b_t, \lambda_t, x_t, \omega_t, \chi_t), \omega_t, \chi_t) \tag{2.12}$$

To simplify notation, I define $z_t^\star \equiv z^\star(k_t, b_t, \lambda_t, x_t, \omega_t, \chi_t)$ and $z_t^0 = z^\star(k_t, 0, 0, x_t, \omega_t, \chi_t)$. The last definition, z_t^0, represents the idiosyncratic shock realization that makes the unlevered firm's value equal to zero, i.e. the highest value of z_t at which the unlevered firm keeps operating.

Deadweight Cost

Upon default, bondholders can seize a fraction $(1-\chi_t) \in [0,1]$ of a firm's value. That is, the higher the stochastic variable χ_t, the lower the bondholders' recovery. At this point χ_t and ω_t are independent although in the data, they may be correlated. As it is described in Section 2.4.2, the points of the grid for χ_t are equally spaced and belong to the interval $[\underline{\chi}, 1]$; where $\underline{\chi}$ and the number of points in the grid are set to match the mean and volatility of recovery rates upon default as in Chen (2010).

To explain the differences in credit spreads and leverage observed empirically between the highest and lowest asset redeployability quintiles (see Table 2.6) as well as the relative importance of ω_t and χ_t, I will look at portfolios that vary by ω_t and χ_t.[14]

Debt Contracts

The firm's creditors buy corporate debt at price $P(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_t)$ and collect coupon and principal payments until the firm defaults. If default occurs at period t, shareholders walk away from the firm, while creditors take over and restructure the unlevered firm incurring proportional deadweight losses χ_t. With these assumptions, period-t per unit market price of debt $P(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_t)$, is pinned down by an arbitrage condition such that the amount of money creditors are willing to pay for the contract must equal the expected value of future payments. Formally, this condition implies the following identity,

$$\begin{aligned} b_{t+1} \times P(k_{t+1}, b_{t+1}, \lambda_{t+1}, \Gamma_t) = & \\ & \mathbb{E}_t \Big(M_{t,t+1} b_{t+1} (\lambda_{t+1} + c + (1-\lambda_{t+1}) \cdot P(k_{t+2}, b_{t+2}, \lambda_{t+2}, \Gamma_{t+1})) \underbrace{\mathbb{I}_{\{z_{t+1} < z_{t+1}^\star\}}}_{\text{solvent states}} \Big) \\ & + \mathbb{E}_t \Big(M_{t,t+1} (1-\chi_{t+1}) J(k_{t+1}, 0, 0, \Gamma_{t+1}) \underbrace{\mathbb{I}_{\{z_{t+1}^\star < z_{t+1} < z_{t+1}^0\}}}_{\text{default states}} \Big) \end{aligned} \tag{2.13}$$

[14] I provide more details about the portfolio construction from the model simulation in Section 2.5.

Importantly, corporate bonds are held by the representative household and are thus valued using the household equilibrium pricing kernel $M_{t,t+1}$. The first term on the right-hand-side of equation (3.6) contains the cash flows received by bondholders if no default takes place at period $t+1$; whereas the second term reflects the payments upon default net of deadweight costs.

2.3.2 Households

The model is completed by specifying the household stochastic discount factor of a representative household who features recursive preferences and consumes according to an exogenous consumption process, C_t. Following Epstein and Zin (1991), the household utility is given by,

$$U_t = \left((1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \mathbb{E}_t \left(U_{t+1}^{1-\gamma} \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right)^{\frac{1}{1-\frac{1}{\psi}}} \tag{2.14}$$

where the preference parameters are the rate of time preference, $\beta \in (0,1)$, the elasticity of intertemporal substitution, ψ, and the coefficient of relative risk aversion, γ. Further, as in Bhamra et al. (2010) and Kuehn and Schmid (2014), aggregate consumption growth is assumed to follow a random walk process with time-varying drift and volatility,

$$\ln\left(C_{t+1}/C_t\right) = g + \mu_c(s_t) + \sigma_c(s_t)\, \eta_{t+1} \tag{2.15}$$

where $\mu_c(s_t)$ and $\sigma_c(s_t)$ depend on the aggregate state of the economy denoted by s_t. The standard normal innovations η_{t+1} are independent of the other stochastic variables of the model. In the numerical solution, the aggregate state s_t is modeled as a persistent Markov chain. The representative household's stochastic discount factor will be computed as,

$$M_{t,t+1} = \beta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left(\frac{W_{t+1}+1}{W_t} \right)^{-(1-\kappa)} \tag{2.16}$$

where W_t denotes the wealth-to-consumption ratio and $\kappa \equiv (1-\gamma)/(1-1/\psi)$. Importantly, the wealth-to-consumption ratio will be a function of the state of the economy, s_t. In fact, it is not difficult to show that $W(s_t)$ solves the system,

$$W(s_t) = \mathbb{E}_t \left(\beta^{\kappa} \left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \left(W(s_{t+1}) + 1 \right)^{\kappa} \Big| s_t \right)^{1/\kappa} \tag{2.17}$$

which is solved through a value-function-iteration procedure conditional on the Markov chain for the aggregate of the economy s_t and the stochastic processes of the remaining model's variables.

2.4 Model parametrization

This section describes the benchmark model calibration and provides details on the functional forms for the adjustment costs $\Phi(\cdot)$ and equity issuances costs $\Psi(\cdot)$. The model is solved using a global method after normalizing all non stationary variables by the aggregate technology shock. Details about the numerical solution and the normalized problem are shown in the Appendix.

2.4.1 Functional forms

Capital adjustment cost

The capital adjustment cost function $\Phi(\cdot)$ is modeled as in Zhang (2005), but adding a degree of risk in the level of partial irreversibility of investment given by $\omega_t > 1$. The capital adjustment cost function is quadratic in the firm's investment rate, and its convexity is determined by $\theta > 0$ and $\theta\omega_t$ when the firm chooses to invest and disinvest, respectively. Formally, $\Phi(\cdot)$ writes,

$$\Phi(k_t, i_t, \omega_t) = k_t \left(\frac{i_t}{k_t} - \delta \right)^2 \left[\mathbb{I}_{\{i_t \geq 0\}} \theta + \mathbb{I}_{\{i_t < 0\}} \theta \omega_t \right] \tag{2.18}$$

In the numerical solution of the model, the stochastic variable ω_t is modeled as a Markov chain with persistence denoted by ρ_ω. Then, a low (high) ω_t implies that the firm's capital investment is highly reversible (irreversible). As is described in Section 2.4.2, the points of the ω_t grid are equally spaced (in logs) and belong to the interval $[1, \bar{\omega}]$; where $\bar{\omega}$ is set to match differences in excess returns showed by the highest and lowest asset redeployability quintiles in the data.

Equity issuance cost

Lastly, I consider a fixed and a proportional equity issuance costs, which are denoted by e_0 and e_1, respectively. Then, the total equity issuance cost is given by the function, $\Psi(e_t) = (e_0 + e_1|e_t|)\mathbb{I}_{\{e_t<0\}}$, where the indicator function $\mathbb{I}_{\{e_t<0\}}$ implies that these costs apply only when the firm is raising new equity finance, that is, when the net payout, e_t, is negative.

2.4.2 Calibration

Standard real business cycles parameters and preference parameters of the benchmark model are set to values taken from the existing literature. The remaining set of parameters are chosen to match aggregate moments and moments derived from sorting firms based on the asset redeployability measure in the data. All parameters values of the monthly calibration implemented are reported in Table 2.1.

Preference parameters are standard in the long-run risk literature (Bansal and Yaron (2004)). The elasticity of intertemporal substitution ψ is set to 2 and the coefficient of relative risk aversion γ is set to 10, as in Kung (2015); and the subjective discount factor β is set to 0.994.

In term of the technology parameters, the productivity process is calibrated following Kuehn and Schmid (2014). Indeed, I model the aggregate Markov chain, s_t, to jointly affect the drift and volatility of the aggregate productivity shock x_t and consumption growth $\ln(C_t/C_{t-1})$. Specifically s_t consists of five states. To calibrate the Markov chain, I set the persistence of the Markov chain (ρ) to 0.95, the mean and volatility of the consumption drift states are set to zero and $8.69e^{-4}/\sqrt{2}$, respectively; and the mean and volatility of the consumption variance states are set to $1.51e^{-4}/\sqrt{2}$ and $1.05e^{-5}/\sqrt{2}$, respectively. Following Kuehn and Schmid (2014), the drift and volatility of aggregate productivity x_t scale with the respective moments of consumption growth by a factor of 1.7. This calibration allows me to match annualized consumption growth moments and obtain a sizable aggregate stock returns volatility. I set g to yield an annual average growth of 1.8%.

At the firm level, the capital share α is set to 0.35, and the depreciation rate of capital δ is set to 1.0%. These values are close to those used in Kung (2015). Firms face proportional costs of production, ϕ, of 0.07 and a fixed cost, f, of 0.05, similar to Kuehn and Schmid (2014) and Gomes et al. (2003a) respectively. As in Zhang (2005) we set the capital adjustment parameter θ to 15. I calibrate the volatility and persistence of the idiosyncratic productivity process to match the annual default rate.

The effective corporate tax rate τ is set to 14%, consistent with the evidence (Binsbergen et al. (2010)). The annual coupon payment, c, is set to 3.0%. Equity issuance cost parameters are set to match the frequency of equity and debt issuance. Lastly, the persistences of the underlying investment irreversibility and deadweight cost processes are set to be high, that is, ρ_ω and ρ_χ are set to 0.9. The remaining parameters controlling the grids of the deadweight cost χ_t and the degree of investment irreversibility ω_t are set as follows. The points of the grid for χ_t are equally spaced in the interval $[\underline{\chi}, 1]$; where $\underline{\chi}$ and the number of points in the grid are set to match the mean recovery rate of 45%, and the volatility of recovery rates of 10% (Chen (2010)). Finally, the points of the grid for ω_t are equally spaced (in logs) and belong to the interval $[1, \bar{\omega}]$; where $\bar{\omega}$ is set to match the difference in excess returns exhibited by the highest and lowest asset redeployability quintiles (see Table 2.6).

2.5 Quantitative results

In this section, I quantitatively assess the importance of both the investment-irreversibility and the deadweight-cost channel as determinants of the cross-sectional credit spreads and leverage. Given that most of the parameters of the model are set to match empirical aggregate moments, I start this section by assessing how the benchmark model performs by comparing the aggregate moments obtained from simulating the model to their empirical counterparts.

To complement the analysis, I report moments of portfolios formed based on asset redeployability from simulated data. The objective of this exercise is to assess whether differences in firms' asset redeployability can generate substantial cross-sectional differences observed in the data.

Next, I decompose credit spreads and leverage of portfolios formed based on asset redeployability from simulated data. Specifically, the goal is to quantify the contribution of each asset redeployability dimension considered in this chapter, i.e. the investment-irreversibility and deadweight-cost channels.

2.5.1 Aggregate moments

Table 2.2 reports the business cycle moments generated from the simulation of the benchmark calibration of the model and compares them with their empirical counterparts. The benchmark calibration generates an average investment-output ratio of 26% which is in line with its 20% obtained from the data. Furthermore, the output volatility $\sigma_{\Delta y}$ and relative macro volatilities are close to the data. The benchmark calibration of the model also replicates correlations across some business cycle variables such as the procyclicality of consumption, and stock returns. The implied persistence of output and investment are also quite close to the ones in the data.

Impulse response functions in Figure 2.1 describe the model dynamics in response to a positive productivity shock. An increase in aggregate productivity Δx leads to positive growth of firms' investment. As showed by Croce (2014), in the context of a model with elasticity of substitution greater than one, a positive shock of the long-run component generates an increases in investment growth which leads to an increase in firm valuation proxies such as the market-to-book ratio as showed by Figure 2.1. The increase in firms' valuation translates to an important increase of the aggregate excess return $(r_e - r_f)$. An increase of the long-run component of the aggregate productivity Δx also raises firms' continuation values so that the number of firms declaring bankruptcy decreases leading to a lower aggregate probability of default. Consistently, credit spreads (cs) also suffer a contraction. As discussed by Chen et al. (2012), after this positive aggregate shock, firms will choose longer debt maturity in order to mitigate costs associated with deadweight losses of default that are more likely to occur in economic downturns when firms are not able to honor their maturing debt.

Table 2.2 also shows key asset pricing moments from the benchmark model's simulations. In particular, the model is able to generate a sizable annual equity risk premium (4.25%), and an important excess returns volatility (7.58%). The strong demand for precautionary savings drives the risk-free rate down to 1.4%, which is below the data, as well as the risk free rate volatility (1.4%). The model generates a sizable credit spreads of 106bps with a volatility of 57bps, both values slightly above their empirical counterparts.

As showed by Table 2.2, and as in the data, credit spreads are counter-cyclical showing a correlation with the output growth of -0.19 which is somewhat below the empirical correlation (-0.36). Table 2.2 also reports several key aggregate corporate financing moments. Specifically, the model generates an annual book leverage of 0.30 and a frequency of equity issuance of 0.15. The unconditional probability of default derived from the model is 1.66%. Overall, the model performs well matching unconditional moments and key dynamics of both macro aggregates and asset prices.

2.5.2 Asset redeployability moments

In this section, I assess the ability of firms' asset redeployability to explain some significant differences in capital structure outcomes. The analysis is conducted by disaggregating moments and impulse response functions by distinct levels of asset redeployability. To understand the strategy followed in this section, let us recall that ω_t and χ_t are modeled independently. Then, in order to assess the importance of the asset redeployability measure through the lens of the quantitative model described in this chapter, I construct three portfolios that are intended to represent a portfolio formed by firms with high, moderate and low degree of asset redeployability. Specifically, from the simulated panel of firms resulted from the model, each period, the high- (low-) asset redeployability portfolio is comprised of firms featuring an investment irreversibility level ω_t and deadweight cost χ_t belonging to the three lowest (highest) set of points of the variable's grids. All the remaining firms are allocated to the portfolio representing firms with a moderate level of asset redeployability.

Table 2.3 reports various moments of the high- and low- asset redeployability portfolios constructed in the model and compared to their empirical counterpart. Both in the model and the data, high asset redeployability firms have higher book leverage, a lower default rate, a lower credit spread, a more procyclical debt maturity structure, and a lower equity return. I will now explain each of these in turn.

Table 2.3 shows that firms with more redeployable assets have larger book leverage ratios than those exhibited by firms with less redeployable assets. Intuitively, firms' enjoying more redeployable assets have higher operating flexibilities which translates to lower probabilities of defaults. Furthermore, in case of default, firms with highly redeployable assets provide more protection to their bondholders since they experience higher recovery rates. Overall, these effects increase firms' debt capacity leading to larger debt-to-asset ratios. The last two columns compare the difference between the high- and low- asset redeployability portfolios in the model and in the data. The cross-sectional difference in the book leverage ratio is 0.056, similar to its empirical counterpart of 0.023. This result is consistent with previous studies (e.g. Benmelech (2008)).

As in the data, the low-asset redeployability portfolio exhibits a more stable debt maturity structure than the high-asset redeployability portfolio does. Low asset redeployability exposes firms to systematic shocks which makes them more concerned with rollover risk associated to short-term debt and thus, these firms prefer to issue long-term debt even when implementing this strategy could be costly. Indeed, firms with less redeployable assets face higher credit spreads. The equilibrium credit spreads of the high-asset redeployability portfolio is lower (85bps) than the credit spreads faced by the low-asset redeployability portfolio (130bps). Note that the magnitude of the difference in the model, -46bps, is larger than its empirical counterpart, i.e. -19bps. This difference can be explained by noticing that the data used is biased towards larger firms.[15] As pointed out by Corhay (2015) credit

[15] As is described in Section 2.6, I compute corporate bond credit spreads from the National Association of Insurance Commissioners (NAIC) bond transaction file which records all public corporate bond transactions by life insurance companies, property and casualty indurance companies, and Health Maintenance Organizations.

spreads on bank loans for small firms is twice as high as the credit spreads of large firms. Moreover, besides the bias of the sample data toward large firms, firms in the sample varies across many more dimensions than those captured in the model and it is likely that these dimensions are not captured by a univariate analysis. To address this concern, in Section 2.6, I run a set of panel regressions that include various controls.

The model also generates substantial differences in equity risk across asset redeployability portfolios. The average excess return is about 3.5% withing high-asset redeployability firms compared to 5.02% within low-asset redeployability firms; which leads to a difference of -1.55%. Notably, in the data, this premium is -0.85%. To understand why the risk premium on equity is lower in firms with more redeployable assets, note that low asset redeployability implies less flexibilities for firms to deploy their excess capital over their lives and in particular when the economy faces bad shocks. In contrast, firms with more redeployable assets do not face the same problem, since they do not have too much excess capital. This lower flexibility is exacerbated in the model since firms also face fixed operating costs in the profit function (as in Carlson et al. (2004)).

In short, the model predicts that firms with highly redeployable assets exhibit higher leverage ratios, and lower credit spreads. These predictions are in line with earlier studies and more importantly, match the data quantitatively.

2.5.3 Assessing asset redeployability channels

In what follows, I use the simulated panels from the model to assess the relative importance of the two aspects of asset redeployability studied in this chapter.

To measure the importance of ω_t and χ_t in shaping debt credit spreads, Table 2.4 Panel A shows the average credit spreads exhibited by firms for each combination of partial irreversibility of investment (ω_t) and deadweight cost (χ_t). As described in the previous section, bold numbers represent the portfolios used to construct the high- and low-asset redeployability portfolios. The last row and column of the table reports the elasticity of credit spreads with respect to changes of ω_t and χ_t, respectively. Elasticities of credit spreads with respect to each variable are intended to capture the percentage change of the portfolio's average credit spreads after a one percentage change of the variable examined, keeping everything else constant. Overall, the larger the degree of investment irreversibility or deadweight costs, the higher the credit spreads of the firm. Furthermore, the sensitivity of credit spreads to changes in ω_t and χ_t increases with the magnitude of each variable. These results capture the notion discussed by Kuehn and Schmid (2014) regarding the convexity of the value of the investment and default option which are convex functions of the state variables. Panel A reveals that both channels reinforce each other by increasing the sensitivity of credit spreads with respect to the other channel. These results show that changes in asset redeployability can be substantial if we consider all possible aspects of firms that can be affected by changes of the assets' liquidity value.

Panel B shows that an increase in investment irreversibility reduces a firm's leverage ratio. As showed in the simple model, this relation is mainly explained by the fact that firms' optimal capital stock decreases substantially when future disinvestment is costly (see Panel C). Unlike the simple model, lower capital stock and higher levels of investment irreversibility also lead to a higher probability of default (Panel D) since the likelihood of reaching the idiosyncratic-shock default threshold increases. Then, an increase of ω_t will not only lower financial needs but also will tend to increase debt credit spreads since default is more likely to occur; this will motivate the firm to decrease the amount of debt issued leading to lower leverage ratios. In contrast, the effect of larger deadweight costs on leverage varies depending on the level of the investment irreversibility faced by the firm. For low levels of ω_t, higher deadweight costs upon default do not have a sizable negative impact on credit spreads and thus, the firm continue to issue debt in order to finance its investment plans. In this case, the low impact of deadweight costs on credit spreads is explained by the small probability of default faced by firms. However, when defaults become more likely after an increase in the investment irreversibility, credit spreads increase importantly in the level of the deadweight cost. Overall, in this case, firms' desire to increase their debt issuances reduces significantly.

Note that unlike the simple model, Panel E shows that the value of recovery rates is not importantly affected by changes in investment irreversibility. However, deadweight costs relate negatively with the value of recovery rates. Two opposite effects explain the apparent independency of the value of recovery rates to investment irreversibility. In fact, despite that the probability of default increases in ω_t, in the model, the unlevered value of the firm upon default decreases in ω_t since the optimal capital stock decreases.

Lastly, Panel H shows that the effect of both channels on excess returns is mixed; however, as is discussed in the previous section, on average the low-asset redeployability portfolio exhibits larger excess returns than the high-asset redeployability portfolio does.

2.6 Panel regressions

In this section, I test in the data the implications of the asset redeployability measure (Kim and Kung (2016)) on credit spreads and leverage ratios predicted by the quantitative model. Also, motivated by the results of the quantitative model that link changes in the value of recovery rates to changes in the deadweight cost, I test the importance of the two channels of asset redeployability documented in the previous section. The strategy is to use a data set of publicly traded bonds to compute firms' credit spreads; while firms' leverage ratios are computed from standard accounting data. To compute the asset redeployability measure, I follow closely Kim and Kung (2016); whereas, expected recovery rates are computed using the KMV model.

2.6.1 Bond sample construction

I obtain corporate bond prices from the National Association of Insurance Commissioners (NAIC) bond transaction file. The NAIC file records all public corporate bond transactions by life insurance companies, property and casualty insurance companies, and Health Maintenance Organizations (HMOs).[16] The database covers from 1994 to 2012.

The first step is to link the NAIC bond transactions table to the Mergent Fixed Income Securities Database (FISD) to obtain bond specific information. The criteria defined to form the final sample is such that it only includes bonds issued by U.S. firms and paying a fixed coupon. As in Campbell and Taksler (2003), bonds with special features such as put, call, exchangeable, asset backed, and convertible are eliminated from the sample. Furthermore, I only keep bonds with an investment grade rating.[17] Following a common practice, I also remove from the sample firms that belongs to the regulated utilities industry and financial institutions. Furthermore, as in Bessembinder et al. (2009), I eliminate transactions smaller than $100,000, sell transactions that involved the bond issuer, and those with the terms *called*, *cancelled*, *conversion*, *direct*, *exchanged*, *issuer*, *matured*, *put*, *redeemed*, *sinking fund*, *tax-free exchange*, and *tendered* in the transaction name field. To eliminate potential data-entry errors contained by the database, I decide to remove observations that show return reversals.[18] Finally, I exclude observations with obvious data errors such as negative price or transaction dates occurring after maturity. Importantly, in cases where there are several bond transactions in a day, the daily bond price is obtained by weighting each transaction price by its volume.

In terms of constructing the credit spreads associated with each transaction, note that the reported prices in the NAIC file are clean bond prices, then accrued interests are added in order to obtain the full settlement price (i.e. the bond dirty price). Transactions' yields are computed by equating the dirty price to the present value of cash-flows.[19] Then, credit spreads are defined in excess of the benchmark treasury at the date of transaction. To obtain the benchmark treasury for each transaction, I match the bond duration to the zero-coupon Treasury yields curve provided by Gürkaynak et al. (2007) - linearly interpolating if necessary. I complement Gürkaynak et al. (2007) database with Treasury yields with maturity shorter than one year by appending the CRSP risk-free series for one and three months. Following Gilchrist and Zakrajšek (2011), I truncate the credit spreads in the sample to be between 5bps and 3,500bps.

Issuers' accounting information are from Compustat and are matched using the six-digit issuer CUSIP. Stock price information is obtained in a similar way from the CRSP file. To ensure that

[16]The NAIC database represents a substantial portion of the corporate bond market. Insurance companies hold between one-third and 40% of issued corporate bonds (Campbell and Taksler (2003)). Bessembinder et al. (2006) estimates that Insurance companies represent a substantial proportion (12.5%) of total bond trading volume. While if the database used is representative can be debatable, I would like to point out that there are other (complementary) sources of bond data; such as Trace US corporate bond database.

[17]Unlike some papers working with the NAIC data base, my results do not depend on whether AAA bonds are excluded or not from the analysis (Campbell and Taksler (2003))

[18]I define return reversal as a return of more than 15% in magnitude immediately followed by a more than 15% return in the opposite direction.

[19]To reconstruct the stream of a bond's cashflows I use either the information about the date of the last coupon payment or the date at which the principal is repaid. To decide which date determines the bond cashflow's timing more precisely I compute accrued interests under both assumptions and compare them to the accrued interest reported by NAIC. The date that reproduces more closely the accrued interests reported by NAIC is used.

all information is included in asset prices, stock returns and bond credit spreads from July of year t to June of year $t+1$ are matched with accounting information for fiscal year ending in year $t-1$. Monthly credit spreads observations are constructed using the last transaction of the month. The sample consists of an unbalanced panel of 16,587 bond-month transactions. Appendix A.1 presents descriptive statistics of the bond sample data used.

2.6.2 Asset redeployability measure

To construct the asset redeployability measure of a firm in a year, I employ the value-weighted average of industry-level redeployability indices obtained from Kim and Kung (2016)[20] across business segments in which the firm operates over the year. To generate this measure every year, I use annual sales information obtained from the Compustat Segment files as weights. Then, the redeployability of assets of firm i at year t, ($\text{Redeployability}_{i,t}$) is computed as,

$$\text{Redeployability}_{i,t} = \sum_{j=1}^{n_{i,t}} w_{i,j,t} \times \text{Redeployability}_{j,t} \tag{2.19}$$

where $n_{i,t}$ is the number of industry segments, and $w_{i,j,t}$ is industry segment j's sales divided by the total sales for firm i in year t.[21] Following Kim and Kung (2016), when information is missing in Compustat Segment files for a firm-year, I use $\text{Redeployability}_{i,t}$ from previous year, and when this information is also missing I impute the asset redeployability measure corresponding to the firm i's industry classification in year t.

2.6.3 Asset redeployability and the cross section of credit spreads

In this section I investigate empirically the effect of the firm's asset redeployability on credit spreads and leverage ratios. The objective is to test the results from the model that relate the degree of asset redeployability negatively to credit spreads and positively to leverage ratios.

To accomplish this objective, I define the variable $\text{Redep}_{i,t-1}$ as a dummy equal to one if the asset redeployability measure of firm i is in the *highest* quintile of the sample distribution of the variable at the previous year to which the observation (i,t) belongs to; and zero otherwise. This specification will facilitate the economic interpretation of the coefficient associated to this variable and also mitigate potential measurement errors on the construction of the asset redeployability measure. Using the monthly panel data, I investigate whether the asset redeployability measure has any predictive power on corporate credit spreads $\text{cs}_{i,t}$ for public debt. To implement this plan, I test the following regression model,

[20]To construct the data on industry-level asset redeployability, Kim and Kung (2016) use the 1997 Bureau of Economic Analysis (BEA) capital flow table. I thank Hyunseob Kim and Howard Kung for making the data available.

[21]This measure of asset redeployability is similar to asset liquidity measures used in Ortiz-Molina and Phillips (2010). Furthermore, Benmelech and Bergman (2009), and Gavazza (2011) implement similar measures for the airline industry.

$$\text{cs}_{i,t} = \alpha + \delta \times \text{Redep}_{i,t-1} + \beta X_{i,t-1} + \varepsilon_{i,t} \tag{2.20}$$

where (i,t) denotes a specific firm-month observation, $\text{Redep}_{i,t-1}$ is the asset redeployability measure described above, and $X_{i,t-1}$ is a vector of controls that will include time, and/or industry fixed effects. The parameter of interest is δ and it will capture the difference in credit spreads, $\text{cs}_{i,t}$, for firms exhibiting high levels of asset redeployability. Additionally, I test a similar regression where book leverage ratio is set as the dependent variable.

In the regressions, controls variables $X_{i,t-1}$ are grouped into three categories: (i) equity characteristics; (ii) bond characteristics; and (iii) macroeconomic variables.[22] Particularly, in the equity controls category I include the mean of the firm excess returns (net of the risk-free rate) computed using the past 12 months of equity returns prior to the month when the transaction occurs. Also, in this category, I include the equity beta; which is computed using the past 36 months of equity returns and value-weighted market returns prior to the month when the transaction occurs. Note that previous literature has shown a positive effect of exposure to systematic risk on credit spreads (Chen et al. (2012)). I also control for well-known determinants of the cross-section of credit spreads including leverage (total debt to capitalization), asset tangibility, book-to-market ratio, the firm size (log-asset), return on assets (ROA), and Tobin's Q. I complement this set of controls with the fitted SIC-based Industry concentration index (Hoberg and Phillips (2010)). Corhay (2015) shows that measures of industry competition affect positively credit spreads.

Bond specific variables include the Altman Z-Score and bond ratings to take into account the overall risk of the firm.[23] Maturity and coupon are also included. Leland and Toft (1996) shows that longer maturity bonds are likely to be risker; whereas Elton et al. (2001) claims that bonds with high coupon payments suffers from higher taxation which should be translated as higher credit spreads. To control for bond-specific illiquidity which can generate an illiquidity premium in my data (Dick-Nielsen et al. (2012)), I include a measure of trading turnover defined as the average of trading volume over the past 12 months as a proportion of total amount outstanding. The log amount outstanding of the bond is also added since a small issue will likely be less liquid.

Finally, I include a series of macroeconomic variables such as three-month Treasury Bill yield. I also include the 36-month moving average and standard deviation of the aggregate market return. Lastly, I also control for the aggregate labor share obtained from Bureau of Labor Statistics (Favilukis et al. (2015)). Further, equity and macroeconomic data are lagged one month to ensure that information is included in credit spreads at the time the bond transaction takes place. All t-statistics are calculated using standard errors clustered at the firm level.

Table 2.7 Columns (4) presents coefficients from estimating the specification of equation (2.20)

[22] It is important to control for all these characteristics because, in contrast to the model, the bond data set exhibits vast heterogeneity in both bond and firm characteristics.

[23] Moody's ratings are converted to numerical values by creating an index starting at 12 (Baa3) and linearly increasing by one for each credit rating notch.

when credit spreads are the dependent variable. The coefficient of interest, δ, reveals that a firm with assets exhibiting a degree of redeployability in the highest asset redeployability quintile is expected to have credit spreads about 30bps lower than others firms, compared to 46bps in the model.

Note that the estimates presented in this section are in line with findings in previous empirical literature that finds that firms with more liquid assets face a lower cost of debt (Ortiz-Molina and Phillips (2010)).

2.6.4 Asset redeployability and the cross section of leverage

Similarly to the previous section, I run the following regression model using annual balance sheet data from Compustat,

$$\text{book leverage}_{i,t} = \alpha + \delta \times \text{Redep}_{i,t-1} + \beta X_{i,t-1} + \varepsilon_{i,t} \tag{2.21}$$

as before, the parameter of interest is δ and it will capture the difference in book leverage, for firms exhibiting high levels of asset redeployability. The independent variables used in this specification are similar to the one already described in the previous section.

Table 2.7 reports the main regression results of this section estimated from the NAIC bond transaction panel. The first column presents coefficients from estimating the specification of equation (2.21). The coefficient of interest, δ, is estimated to be around 2.2% and is statistically significant. That is, a firm with assets exhibiting a degree of redeployability in the highest asset redeployability quintile is expected to have a leverage ratio, on average, 2.2 percentage points higher than other firms. Table 2.3 shows that the calibrated model reflects a similar effect of asset redeployability on leverage. Indeed, the difference between the leverage ratio of the high- and low-asset redeployability portfolio in the simulated data is, on average, 5.6 percentage points.

Importantly, the estimates presented are in line with findings in previous empirical literature that finds that firms with more liquid assets exhibit larger leverage ratios.

2.6.5 Asset redeployability decomposition

In the model, the value of recovery rate relates importantly to deadweight costs, χ_t. In this section, I use this result to motivate a decomposition of the asset redeployability measure, $\text{Redeployability}_{i,t}$, in two components: (i) a component that contains information about expected recovery rates and (ii) a component that is not able to predict expected recovery rates, $\text{Redeployability(residual)}_{i,t}$.

Specifically, I start running a specification similar to the those described by equations (2.20) and (2.21), but now the coefficient δ is separated in two based on the estimation of an intermediate regression. This intermediate regression allows me to find the component of asset redeployability that does not explain expected recovery rates; and thus to test the following specification,

$$\begin{aligned} \text{Y}_{i,t} &= \alpha + \delta_0 \times \text{Redep(residual)}_{i,t-1} + \delta_1 \times \text{E(recovery rate)}_{i,t-1} + \beta X_{i,t-1} + \varepsilon_{i,t} \\ \text{Redeployability}_{i,t-1} &= \gamma \times \text{E(recovery rate)}_{i,t-1} + \text{Redeployability(residual)}_{i,t-1} \end{aligned} \tag{2.22}$$

where the independent variable $\text{Y}_{i,t}$ is either the credit spreads or the book leverage ratio; furthermore, $\text{Redep(residual)}_{i,t-1}$ is defined as a dummy equal to one if the component of asset redeployability that is not explained by recovery rates is in the highest quintile of the sample distribution of the variable at the previous year to which the observation (i,t) belongs to; and zero otherwise. The final goal is to test empirically whether or not credit spreads and book leverage are explained by other firms' characteristics linked to asset redeployability apart from deadweight cost at default; such as, operating flexibilities related to the firms' ability to adapt their operations. To accomplish this goal, first I start describing how expected recovery rates were computed.

Expected recovery rates

Following Altman et al. (2004) and Bohn and Crosbie (2003), a measure of expected recovery rates is derived from adjusting a Merton-like default model to firms' observations in the data. Specifically, the method applied estimates the parameters of the KMV model by solving a system of equations for each observation of the database used. Appendix A.1 provides technical details of the model implemented.

Intuitively, the system of equations corresponds to two identities derived from a set of assumptions regarding the dynamic of a firm's assets, debt structure, and market perfection. The system of equations uses a set of observable variables, i.e. the value and volatility of equity in conjunction with total debt, to estimate the value and volatility of the firm's assets (unobservable). The general idea is based on the notion that firm's equity is a call option on the the firm's assets. Once the value and volatility of the firm's assets are estimated, expected recovery rates are computed as the expected ratio of the asset value to the total debt conditional on default.

Asset redeployability decomposition and credit spreads

Table 2.8, column (4), presents coefficients from estimating the specification in equation (2.22) when the dependent variable $Y_{i,t}$ represents credit spreads. The coefficient δ_1 reveals that a higher expected recovery rate allows firms to reduce their credit spreads. Moreover, the coefficient δ_0 shows that the asset redeployability measure contains information that is not related to recovery rates but still correlates negatively with credit spreads. Specifically, the coefficients δ_0 shows that firms in the highest quintile of the asset redeployability component that does not relate to recovery rates exhibits lower credit spreads.

Despite that both coefficients δ_0 and δ_1 are statistically significant, the expected recovery rates variable seems to affect less credit spreads. Indeed, reducing credit spreads in δ_0 basis points requires a two-SD increase in expected recovery rates; whereas to have a similar effect, the asset redeployability component of a firm that does not relate to recovery rates must show less than a one-SD increase so that the dummy Redep(residual)$_{i,t-1}$ becomes equal to one. Importantly, in the data, these results stays economically and statistically significant, even after controlling for many variables used to predict credit spreads and leverage.

In the model, Table 2.4 Panel A shows a similar effect. The elasticities of credit spreads to changes in investment irreversibility are larger than elasticities of credit spreads to the deadweight costs.

Asset redeployability decomposition and book leverage

The first column of Table 2.8 reports the main regression results from estimating the specification (2.22) when the dependent variable $Y_{i,t}$ represents the book leverage ratio. The coefficients of interest, δ_0 and δ_1, are estimated to be around 2.2% and -0.2%, and are statistically significant. That is, a firm with assets exhibiting a degree of redeployability in the highest quintile is not only expected to have a book leverage ratio on average 2.2 percentage points larger than other firms (see Table 2.7); Table 2.8 also shows that this positive effect comes mainly from aspects of the firm that relate to its asset redeployability but are different from expected recovery rates.

To the extent that within the model expected recovery rates are primarily related to the deadweight cost χ_t, Table 2.4 shows that the calibrated model generates implications for leverage ratios that are in line with the one presented in this section. Table 2.4 Panel B shows that in the model firms' leverage ratios vary mainly due to changes in investment irreversibility. In contrast, in the model, deadweight costs shows mixed effects on explaining firms' leverage ratios.

2.7 Conclusion

By affecting the liquidation value of a firm's assets, low asset redeployability increases both the cost of disinvesting of an operating firm, as well as the cost of corporate default by decreasing the value at which a distressed firm can liquidate its assets. Motivated by these two aspects of a firm affected by the redeployability of its assets, this chapter studies the importance of asset redeployability on determining leverage ratios and credit spreads through two main channels; that is, the investment-irreversibility and the deadweight-cost channel.

Using a production-based asset-pricing model that incorporates varying degrees of investment irreversibility and deadweight costs, this chapter shows that even though both channels affect credit spreads positively, the importance of the deadweight-cost channel depends on the degree of investment irreversibility. Credit spreads are affected by deadweight costs as long as the level of investment irreversibility imposes significant real frictions to the firm over its life, increasing its probability of default. Further, the model reveals that the positive link between leverage ratios and asset redeployability is mainly driven by the investment-irreversibility channel. In most of the cases, an increase in deadweight costs is not enough to affect significantly a firm's investment decisions and thus, the firm continues issuing debt to fund its financial needs.

Despite that the model is calibrated to match a set of aggregate moments and to replicate cross-sectional differences in excess returns exhibited by the highest and lowest asset redeployability quintiles,[24] the resulted magnitudes across portfolios formed based on the degree of asset redeployability for leverage ratios and credit spreads accord with the existing empirical literature. I verify the model's predictions using a panel of publicly corporate bond transactions in conjunction with standard accounting data. In the data, I find that asset redeployability decreases credit spreads by 30bps and increases leverage ratios by 2.2 percentage points. Also, credit spreads and leverage ratios show to be more sensitive to the asset redeployability's component that is not related to expected recovery rates. These results are robust to various controls.

[24] As is described in Section 2.4.2, the deadweight-cost channel is modeled as a Markov chain where the number of points in the grid is set to match the mean and volatility of recovery rates as in Chen (2010).

Table 2.1: Benchmark monthly calibration

Parameter	Description	Value
A. Preferences		
β	discount factor	0.994
γ	relative risk aversion	10.0
ψ	elasticity of intertemporal substitution	2.0
B. Production		
α	capital share	0.35
δ	capital depreciation rate	0.01
f	operational (fixed) cost	0.05
ϕ	operational (linear) cost	0.07
θ	capital adjustment cost parameter	15
ρ_ω	persistence of the asset redeployability state ω_t	0.90
ρ_χ	persistence of the recovery rate state χ_t	0.90
C. Productivity		
g	growth rate of consumption	0.018/12
ρ	persistence of aggregate state s_t	0.95
σ_z	conditional volatility of the idiosyncratic shock	0.13
ρ_z	persistence of idiosyncratic shock	0.90
D. Finance		
τ	tax rate	0.14
c	coupon rate	3.0%/12
e_0	equity issuance cost: fixed component	0.06
e_1	equity issuance cost: linear component	0.03

Benchmark monthly calibration. This table reports the parameter values used in the benchmark monthly calibration of the model. Section 2.4 describes the moments targeted to set each parameter.

Table 2.2: Aggregate business cycle, asset pricing and financing moments

Moment	Data	Model	Moment	Data	Model
A. Business cycle					
$E(\Delta y)(\%)$	1.80	1.55	$corr(\Delta c, \Delta y)$	0.39	0.49
$\sigma_{\Delta y}(\%)$	3.56	3.69	$corr(\Delta c, r_e - r_f)$	0.25	0.43
$E(I/Y)$	0.20	0.26			
$\sigma_{\Delta c}/\sigma_{\Delta y}$	0.71	0.79	$ACF_1(\Delta y)$	0.35	0.33
$\sigma_{\Delta i}/\sigma_{\Delta y}$	4.50	4.30	$ACF_1(\Delta i)$	0.85	0.80
$E(\text{maturity})(\text{yrs})$	7.6	4.7	$\sigma(\text{maturity})(\text{yrs})$	11.3	9.4
B. Asset prices					
$E(r_e - r_f)(\%)$	7.22	4.25	$\sigma(r_e - r_f)(\%)$	16.5	7.58
$E(r_f)(\%)$	1.51	1.40	$\sigma(r_f)(\%)$	2.2	1.4
$E(cs)(\text{bps})$	90	106	$\sigma(cs)(\text{bps})$	44	57
C. Financing					
Book leverage	0.26	0.30	$corr(\text{equity payout}, \Delta y)$	0.45	0.35
Freq. of equity issuance	0.09	0.15	$corr(\text{debt repurchase}, \Delta y)$	-0.70	-0.37
Default rate (%)	$0.84^{\dagger}$	0.85	$corr(cs, \Delta y)$	-0.36	-0.19

Aggregate business cycle, asset pricing and financing moments. I/Y denotes the investment-output ratio. Δy, Δc, Δi denote output, consumption, and investment growth respectively. Average and standard deviation of debt maturity exhibited by the data is computed directly from the Mergent's Fixed Income Security Database (FISD). $r_e - r_f$ is the aggregate stock market excess return, r_f is the one-period real risk-free rate, and cs is the aggregate credit spreads. Debt repayment and equity payout are normalized by total assets. Data moments are obtained from Jermann and Quadrini (2009) and Chen (2010). Model moments are calculated by simulating the model for 3,000 firms and 6,000 months, with a 1,000 months burning period. Aggregate returns and credit spreads are equally-weighted. Growth rates, and returns moments are annualized percentage, credit spreads are in annualized basis point units.
† The average default rate reported correspond to average expected default rates resulted from implementing the KMV model in the panel data described in Section 3.2.1. Appendix A elaborates on the technical details of the KMV model used.

Table 2.3: Asset redeployability moments

	Simulated Moments		High minus Low	
	High AR	Low AR	Data	Model
Book Leverage	0.308	0.252	0.023	0.056
Market Leverage	0.240	0.234	-0.008	0.006
Default rate (%)	0.788	0.978	-0.310[†]	- 0.190
Recovery rates (%)	0.534	0.407	-0.182[†]	-0.127
$corr(\text{maturity}, \Delta y)$	0.710	0.350	0.250	0.360
$E(cs)$(bps)	85	130	-19	-46
$E(r_i - r_f)$(%)	3.465	5.015	-0.850	-1.550

Asset redeployability moments. This table reports key moments of extreme asset redeployability portfolios. Model moments are calculated by simulating the model for 3,000 firms and 6,000 months, with a 1,000 months burning period. From the simulated data, each period the high- (low-) asset redeployability portfolio is comprised of firms with an investment irreversibility level ω_t and deadweight cost χ_t belonging to the three lowest (highest) values of ω_t and χ_t, respectively. Market leverage is obtained as the ratio of the debt market value and the sum of the equity and debt market values. The market value of debt is defined as total debt times the market value of 1$ of debt obtained from my data sample. The remaining variables are described in Table 2.2.

[†] The default and recovery rates used to compute the difference reported correspond to expected default and recovery rates resulted from implementing the KMV model in the panel data described in Section 3.2.1. Appendix A elaborates on the technical details of the KMV model.

Table 2.4: Portfolios sorted by investment irreversibility and deadweight cost

Panel A: CREDIT SPREADS (cs)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta cs/\%\Delta\chi$
$\omega_1 = 1$	**77.0**	**79.5**	**80.5**	81.6	83.3	86.0	90.7	0.11
ω_2	**82.5**	**84.8**	**85.6**	86.7	88.3	90.4	95.3	0.10
ω_3	**88.0**	**90.3**	**92.4**	94.9	98.4	104.3	116.1	0.19
ω_4	93.5	95.8	98.2	101.1	105.2	112.0	125.7	0.20
ω_5	99.5	101.8	104.1	107.0	**111.8**	**119**	**133.2**	0.20
ω_6	105.5	107.5	110.5	113.9	**119.5**	**127.7**	**144.1**	0.22
$\omega_7 = \bar{\omega} = 3.8$	111.5	113.5	116.7	120.4	**126.3**	**136.3**	**153.8**	0.22
$\%\Delta cs/\%\Delta\omega$	0.25	0.24	0.26	0.27	0.29	0.32	0.37	

Panel B: BOOK LEVERAGE RATIO (b/k)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta(b/k)/\%\Delta\chi$
$\omega_1 = 1$	**0.32**	**0.32**	**0.32**	0.33	0.34	0.34	0.35	0.06
ω_2	**0.31**	**0.31**	**0.31**	0.31	0.32	0.32	0.32	0.01
ω_3	**0.29**	**0.29**	**0.29**	0.29	0.29	0.29	0.28	-0.03
ω_4	0.27	0.27	0.27	0.27	0.26	0.26	0.26	-0.05
ω_5	0.26	0.26	0.26	0.26	**0.26**	**0.25**	**0.25**	-0.03
ω_6	0.26	0.25	0.25	0.25	**0.25**	**0.25**	**0.25**	-0.02
$\omega_7 = \bar{\omega} = 3.8$	0.25	0.25	0.25	0.25	**0.25**	**0.25**	**0.25**	-0.01
$\%\Delta(b/k)/\%\Delta\omega$	-0.16	-0.17	-0.17	-0.18	-0.2	-0.21	-0.22	

Panel C: INVESTMENT RATE (i/k)

ω	$\chi_1 = \underline{\chi}$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta(i/k)/\%\Delta\chi$
$\omega_1 = 1$	**0.055**	**0.058**	**0.054**	0.055	0.048	0.052	0.045	-0.12
ω_2	**0.038**	**0.039**	**0.038**	0.038	0.035	0.029	0.027	-0.23
ω_3	**0.030**	**0.025**	**0.026**	0.028	0.021	0.026	0.023	-0.13
ω_4	0.019	0.021	0.021	0.014	0.018	0.018	0.010	-0.27
ω_5	0.009	0.010	0.011	0.006	**0.007**	**0.008**	**0.011**	0.33
ω_6	0.004	0.008	0.008	0.004	**0.005**	**-0.001**	**0.000**	-0.80
$\omega_7 = \bar{\omega} = 3.8$	0.003	-0.001	0.002	0.001	**0.002**	**0.001**	**0.002**	-2.89
$\%\Delta(i/k)/\%\Delta\omega$	-1.46	-1.81	-1.52	-1.82	-1.55	-3.41	-6.93	

(continues)

Panel D: DEFAULT PROBABILITY (CONDITIONAL ON DEFAULT) IN BPS (PD)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta PD/\%\Delta\chi$
$\omega_1 = 1$	**77.1**	**73**	**73.9**	76.7	77.6	65.3	61.4	-0.12
ω_2	**79.2**	**77.7**	**76.7**	70.6	75.0	71.5	64.9	-0.08
ω_3	**82.1**	**85.6**	**84.0**	78.6	84.8	81.8	69.9	00
ω_4	87.6	84.6	87.1	82.9	90.4	89.8	76.5	0.02
ω_5	92.8	92.2	91.1	85.9	**98.2**	**88.7**	**77.6**	-0.02
ω_6	95.9	93.7	93.1	88.5	**98.2**	**98.1**	**80.9**	0.02
$\omega_7 = \bar{\omega}$ =3.8	97.4	95.2	92.1	97.7	**101.5**	**101.9**	**80.9**	0.04
$\%\Delta PD/\%\Delta\omega$	0.16	0.19	0.15	0.17	0.19	0.31	0.19	

Panel E: VALUE OF THE RECOVERY RATE (CONDITIONAL ON DEFAULT) IN BPS (RR)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta RR/\%\Delta\chi$
$\omega_1 = 1$	**55.4**	**54.6**	**50.7**	46.2	45.6	36.0	0.0	-0.32
ω_2	**55.1**	**53.4**	**51.3**	47.6	45.6	36.0	0.0	-0.32
ω_3	**55.2**	**53.7**	**51.3**	47.3	45.6	36.0	0.0	-0.32
ω_4	55.1	53.3	51.0	47.1	45.6	36.0	0.0	-0.32
ω_5	55.1	53.5	51.4	47.5	**45.6**	**36.0**	**0.0**	-0.32
ω_6	55.1	53.3	51.3	47.2	**45.6**	**36.0**	**0.0**	-0.32
$\omega_7 = \bar{\omega}$ =3.8	54.0	51.8	51.0	48.0	**45.0**	**36.0**	**0.0**	-0.30
$\%\Delta RR/\%\Delta\omega$	-0.02	-0.03	0.0	0.03	-0.01	0.0	-	

Panel F: CREDIT RISK IN BPS (CR)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	χ_7 =1	$\%\Delta CR/\%\Delta\chi$
$\omega_1 = 1$	**55.3**	**61.1**	**57.3**	51.1	51.3	56.7	29.3	0.03
ω_2	**58.4**	**60.4**	**60.2**	63.7	58.9	55	30.4	-0.04
ω_3	**61.1**	**58.3**	**59.7**	63.6	59.2	58.5	46.2	-0.03
ω_4	60.9	64.4	62.2	65.3	60.3	58.2	49.2	-0.03
ω_5	61.8	63.0	64.3	68.6	**59.2**	**66.3**	**55.7**	0.07
ω_6	64.7	67.1	68.7	72.7	**66.9**	**65.6**	**63.2**	0.02
$\omega_7 = \bar{\omega}$ =3.8	68.1	70.1	75.6	70.7	**69.7**	**70.4**	**72.9**	0.03
$\%\Delta CR/\%\Delta\omega$	0.14	0.1	0.19	0.24	0.22	0.15	0.7	

(continues)

Panel G: DEBT AVERAGE MATURITY (m) IN YEARS

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta m/\%\Delta\chi$
$\omega_1 = 1$	**2.40**	**3.05**	**3.51**	3.43	3.32	3.75	5.54	0.65
ω_2	**2.89**	**3.31**	**3.54**	3.42	3.25	3.89	7.57	0.85
ω_3	**3.56**	**3.78**	**3.85**	3.82	3.79	4.02	4.74	0.20
ω_4	4.64	4.40	4.36	4.40	4.46	4.42	4.32	-0.05
ω_5	4.52	4.70	4.72	4.76	**4.83**	**4.79**	**4.70**	0.03
ω_6	4.47	4.87	4.88	4.89	**4.92**	**4.90**	**4.87**	0.06
$\omega_7 = \bar{\omega} = 3.8$	4.42	5.05	5.05	5.06	**5.06**	**5.06**	**5.05**	0.1
$\%\Delta m/\%\Delta\omega$	0.46	0.36	0.25	0.27	0.3	0.21	0.04	

Panel H: EXPECTED EXCESS RETURNS ($E(r_i - r_f)$)

ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta E(r_i - r_f)/\%\Delta\chi$
$\omega_1 = 1$	**3.10**	**3.57**	**3.60**	2.93	3.81	3.63	3.74	0.17
ω_2	**3.33**	**3.79**	**3.34**	3.93	3.38	3.46	4.09	0.17
ω_3	**3.69**	**3.99**	**4.01**	3.54	4.43	3.85	4.31	0.14
ω_4	4.01	3.91	4.10	4.68	4.11	4.93	5.49	0.24
ω_5	4.61	4.72	4.20	4.16	**4.46**	**4.82**	**4.85**	0.04
ω_6	4.57	4.37	4.76	4.82	**4.91**	**4.73**	**5.90**	0.19
$\omega_7 = \bar{\omega} = 3.8$	5.23	4.59	4.85	5.01	**4.86**	**5.71**	**5.56**	0.06
$\frac{\%\Delta E(r_i - r_f)}{\%\Delta\omega}$	0.37	0.19	0.22	0.43	0.2	0.34	0.31	

Portfolios sorted by investment irreversibility and deadweight cost. This table reports average credit spreads, book leverage, investment rate, default probability, value of recovery rate, credit risk, average maturity and excess returns for portfolios formed by grouping simulated firms based on their partial irreversibility of investment, ω_t, and deadweight cost, χ. The model is simulated for 3000 firms and 6,000 months, with a 1,000 months burning period. The Markov chain of χ_t includes seven equally-spaced points. The Markov chains of ω_t includes seven equally-spaced points in logs. Bold numbers represent the portfolios used to construct the high- and low-asset redeployability portfolios in Table 2.3. The last row (column) in each table shows the elasticity of the moment reported respect to changes on ω_t (χ_t).

Table 2.5: Credit spreads by investment irreversibility and recovery rates (short-term debt)

	χ							
ω	$\chi_1 = \underline{\chi} = 0.18$	χ_2	χ_3	χ_4	χ_5	χ_6	$\chi_7 = 1$	$\%\Delta cs/\%\Delta\chi$
$\omega_1 = 1$	**41.0**	**43.5**	**44.5**	48.0	48.3	48.4	48.4	-0.11
ω_2	**43.5**	**45.8**	**46.7**	50.1	50.4	50.5	50.5	-0.10
ω_3	**44.8**	**47.1**	**47.6**	45	45.1	45.2	45.2	-0.01
ω_4	47.0	49.3	49.9	50.3	47.6	45.1	42.8	0.06
ω_5	56.3	58.5	59.2	59.6	**56.1**	**52.7**	**49.7**	0.08
ω_6	62.4	64.4	65.2	65.6	**61.5**	**57.6**	**54.1**	0.09
$\omega_7 = \bar{\omega} = 3.8$	70.6	72.6	73.4	73.9	**70.5**	**67.2**	**64.1**	0.06
$\%\Delta cs/\%\Delta\omega$	0.38	0.36	0.35	0.31	0.28	0.24	0.21	

Credit spreads by investment irreversibility and recovery rates (short-term debt). This table reports information described in Table 2.4 for the case where the parameter controlling firms' debt maturity is set to $\lambda = 1$. That is, firms are forced to issue short-term debt. Model moments are calculated by simulating the model for 3000 firms and 6,000 months, with a 1,000 months burning period.

Table 2.6: Univariate analysis

	High Redeployability		Low Redeployability		Test of differences	
	Mean	Median	Mean	Median	t-test	Wilcoxon test
Redeployability	0.42	0.39	0.21	0.23		
Yield Spread	118 bps	108 bps	137 bps	126 bps	5.41***	9.48***
Book Leverage	0.265	0.247	0.242	0.269	-7.06***	-3.96***
$E(r_i - r_f)$	8.49 %	6.86 %	9.34 %	11.27 %	1.16	3.65***

Univariate analysis. Panel A reports the means and medians of asset redeployability measure, yield spreads and excess returns aggregated across all firms/months of the NAIC data is from 1994 and 2012. High Redeployability corresponds to the highest asset redeployability quintile and Low Redeployability to the lowest asset redeployability quintile. The yield spreads is defined as the bond yield in excess of a government bond with equal duration and $r_i - r_f$ is the annualized realized stock return over the following year in excess of the monthly bill. The last two columns of the table present test statistics of the t-test and the Wilcoxon test of the differences in mean and median across the two samples. Panel B documents the correlations between the annual (seasonally adjusted) percentage change of gross value added of nonfinancial corporate business and five variable of the highest and lowest redeployability quintiles: cash-to-asset, investment-to-asset, total debt-to-asset, equity-to-asset and long-term debt share. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2.7: Asset redeployability and the cross-section of capital structure outcomes

	Leverage	Yield spreads (bps)			
		(1)	(2)	(3)	(4)
Asset Redeployability	0.022***	-10.18**	-28.74**	-29.3***	-28.84***
	(3.65)	(-2.28)	(-2.29)	(-2.65)	(-2.64)
Mean excess return (%)	0.001**	-5.47***	-4.4***	-5.46***	-5.53***
	(-2.13)	(-13.64)	(-5.35)	(-6.86)	(-6.92)
Market Beta	-0.005***	-8.6***	20.49***	13.06**	12.61*
	(-3.36)	(-4.14)	(2.75)	(2.01)	(1.95)
Leverage		140.01***	82.68*	38.76	37.71
		(9.11)	(1.85)	(1.23)	(1.2)
Tangibility	0.234***	-36.15***	-21.86	-4.32	-4.05
	(22.14)	(-3.11)	(-0.93)	(-0.2)	(-0.19)
Book-to-Market (log)	-0.053***	4.67	8.29	10.65	10.43
	(-15.18)	(1.4)	(0.8)	(1.06)	(1.03)
Asset Size (log)	0.023***	-0.34	-10.45***	8.29**	8.13**
	(19.98)	(-0.21)	(-2.73)	(2.29)	(2.25)
ROA (%)	0	-2.14***	-1.26	-0.39	-0.38
	(-0.35)	(-6.34)	(-1.42)	(-0.48)	(-0.47)
Tobin's Q	-0.039***	-4.33***	-5.13	-1.49	-1.45
	(-27.33)	(-2.6)	(-1.02)	(-0.3)	(-0.29)
Concentration	0.001***	0.03	0.16	0.18	0.17
	(9.15)	(0.47)	(0.78)	(1.15)	(1.1)
Bond characteristics					
Z-Score	-0.009***	17.79***	12.45	15.31**	15.12**
	(-8.58)	(5.66)	(1.38)	(2.07)	(2.04)
Credit rating				-17.12***	-17.19***
				(-8.96)	(-8.97)
Years to maturity				1.03***	1.02***
				(6.67)	(6.71)
Coupon rate (%)				10.95***	10.81***
				(8.97)	(8.83)
Issue size (log)				-4.92*	-4.86*
				(-1.9)	(-1.9)
Trading turnover (log)				1.06*	1.02*
				(1.79)	(1.71)
Macroeconomic variables					
Three-month T-Bill yield (%)	0.004*		-0.99	1.08	1.17
	(1.75)		(-0.46)	(0.69)	(0.75)
Vol. of daily index ret (%)	0.064**		15.59***	17.11***	17.24***
	(2.29)		(6.92)	(7.41)	(7.4)
Mean of daily index ret (%)	0.045		-15.18***	-13.33***	-13.01***
	(1.19)		(-5.22)	(-4.76)	(-4.73)
Labor Share (%)	-0.168***		8.53***	8.06***	7.53***
	(-2.7)		(9.78)	(9.67)	(9.33)
Constant	-0.249*	278.7***	298.45***	343.44***	341.75***
	(-1.91)	(9.68)	(6.05)	(4.83)	(4.8)
Observations	40534	14418	14418	14418	14418
R^2	0.26	0.27	0.35	0.41	0.42
Time FE	Yes	No	No	No	Yes
Industry FE	No	Yes	Yes	Yes	Yes

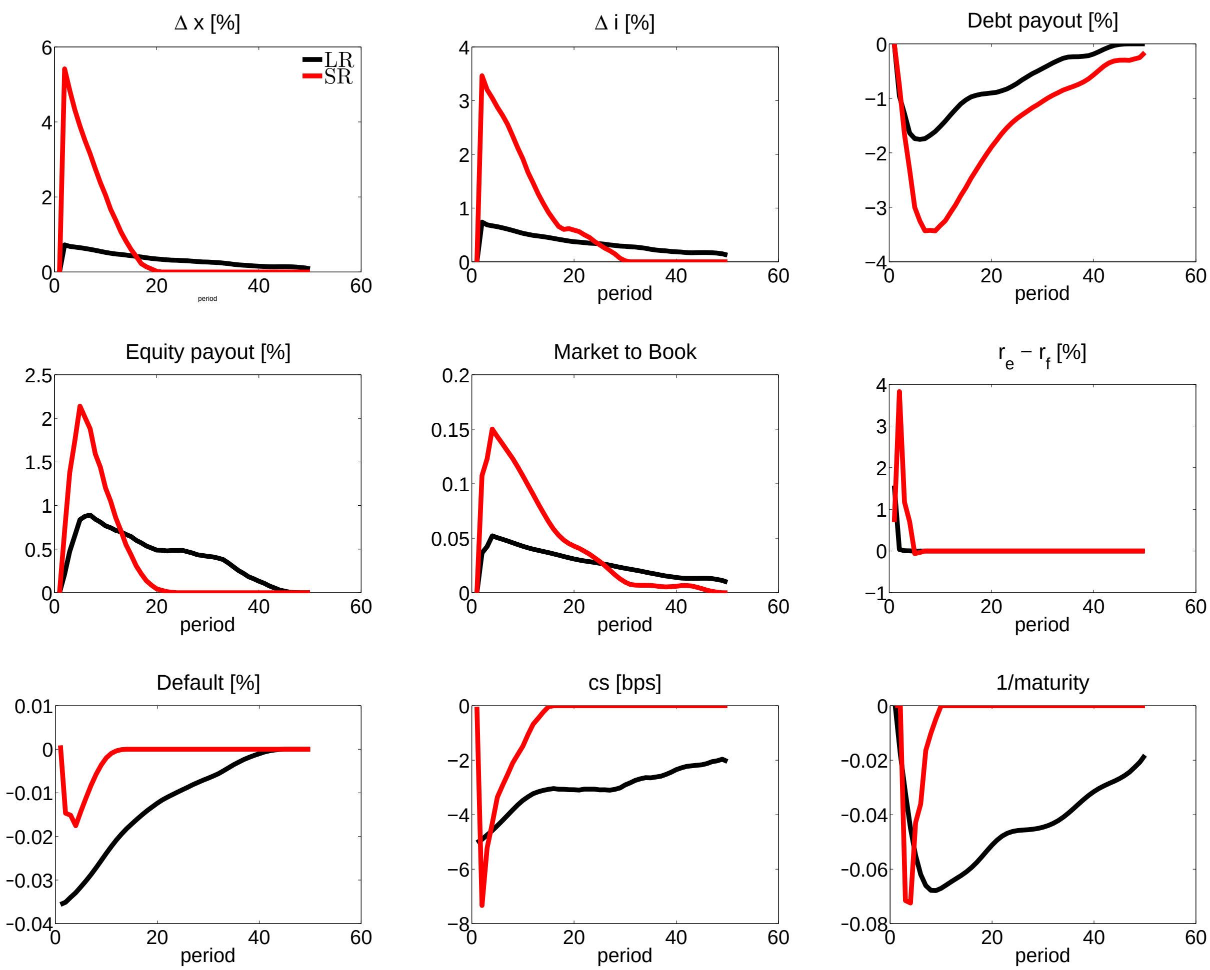
Asset redeployability and cross-section of capital structure outcomes. The controls variables are grouped into three categories: (i) equity characteristics; (ii) bond characteristics; and (iii) macroeconomic variables. Variable descriptions are given in Section 3.2.1 and Appendix A.

Table 2.8: Asset redeployability channels and the cross-section of capital structure outcomes

	Leverage	Yield spreads (bps)			
		(1)	(2)	(3)	(4)
Asset Redeployability (residual)	0.022***	-21.17***	-21.75*	-21.49**	-22.6**
	(3.6)	(-4.14)	(-1.88)	(-2)	(-2.14)
Expected recovery rate	-0.002***	-4.86***	-3.61**	-3.29**	-3.36**
	(-9.01)	(-14.17)	(-2.32)	(-2.26)	(-2.29)
Mean excess return (%)	-0.003***	-4.84***	-4.21***	-5.2***	-5.28***
	(-9.76)	(-12.49)	(-5.7)	(-6.95)	(-7.01)
Market Beta	0.001	-11.69***	15.83**	8.43	7.8
	(-1.12)	(-6.03)	(2.17)	(1.29)	(1.2)
Leverage		87.19***	81.14	42.53	40.56
		(5.35)	(1.54)	(1.13)	(1.07)
Tangibility	0.079***	-46.41***	-31.58	-16.77	-16.73
	(7.28)	(-4.2)	(-1.19)	(-0.88)	(-0.88)
Book-to-Market (log)	-0.06***	6.43*	8.59	11.51	11.29
	(-14.85)	(1.91)	(0.84)	(1.11)	(1.09)
Asset Size (log)	0.008***	0.68	-9.22***	7.49**	7.34**
	(6.47)	(0.44)	(-2.61)	(2.41)	(2.37)
ROA (%)	0.001***	-1.68***	-0.93	-0.15	-0.14
	(3.75)	(-5.23)	(-1.08)	(-0.18)	(-0.16)
Tobin's Q	-0.05***	-5.76***	-3.91	1.98	1.96
	(-16.86)	(-3.25)	(-0.67)	(0.33)	(0.33)
Concentration	0	0.05	0.17	0.16	0.14
	(1.53)	(0.68)	(0.74)	(0.85)	(0.78)
Bond characteristics					
Z-Score	-0.022***	16.4***	13.1	15.95**	15.72**
	(-10.53)	(5.1)	(1.41)	(2.02)	(1.98)
Credit rating				-17.17***	-17.26***
				(-7.61)	(-7.61)
Years to maturity				1.06***	1.05***
				(6.45)	(6.51)
Coupon rate (%)				10.58***	10.44***
				(8.48)	(8.36)
Issue size (log)				-3.77	-3.71
				(-1.55)	(-1.53)
Trading turnover (log)				1.25**	1.2*
				(2.06)	(1.97)
Macroeconomic variables					
Three-month T-Bill yield (%)	-0.007***		-2.02	0.16	0.2
	(-3.31)		(-0.81)	(0.08)	(0.11)
Vol. of daily index ret (%)	0.048**		11.27***	13.37***	13.4***
	(2.31)		(4.58)	(6)	(5.94)
Mean of daily index ret (%)	0.058*		-15.31***	-13.3***	-12.85***
	(1.68)		(-4.54)	(-4.33)	(-4.29)
Labor Share (%)	-0.129***		7.84***	7.62***	6.82***
	(-2.81)		(9.05)	(9.38)	(8.42)
Constant	0.247**	734.38***	646.06***	657.39***	663.39***
	(2.34)	(17.8)	(4.03)	(3.69)	(3.69)
Observations	21996	13436	13436	13436	13436
R^2	0.16	0.29	0.36	0.42	0.43
Time FE	Yes	No	No	No	Yes
Industry FE	No	Yes	Yes	Yes	Yes

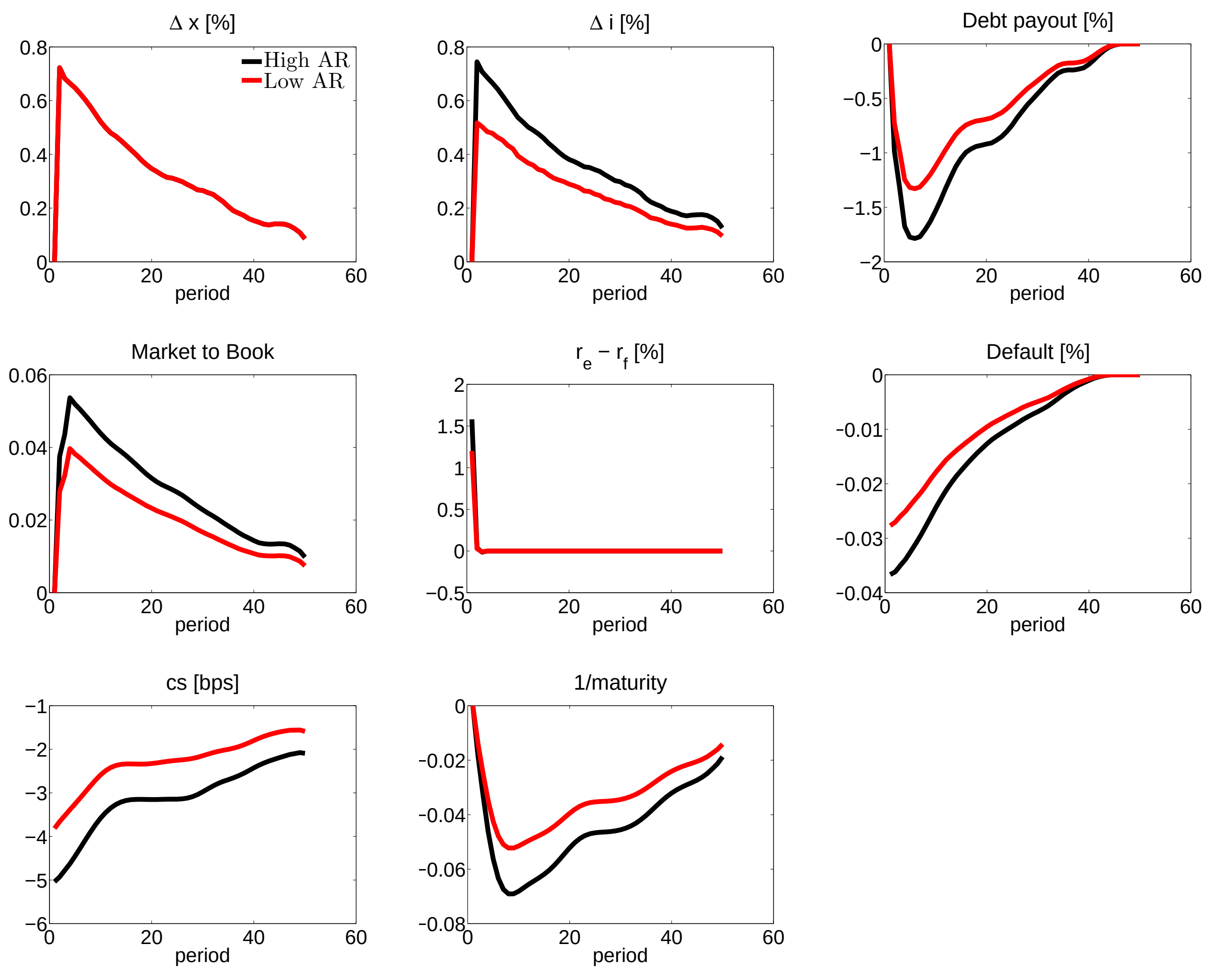
AR channels and the cross-section of capital structure outcomes. First two control variables are described in Section 2.6. Refer to Table 2.7 for remaining variables.

Figure 2.1: Aggregate impulse-response functions



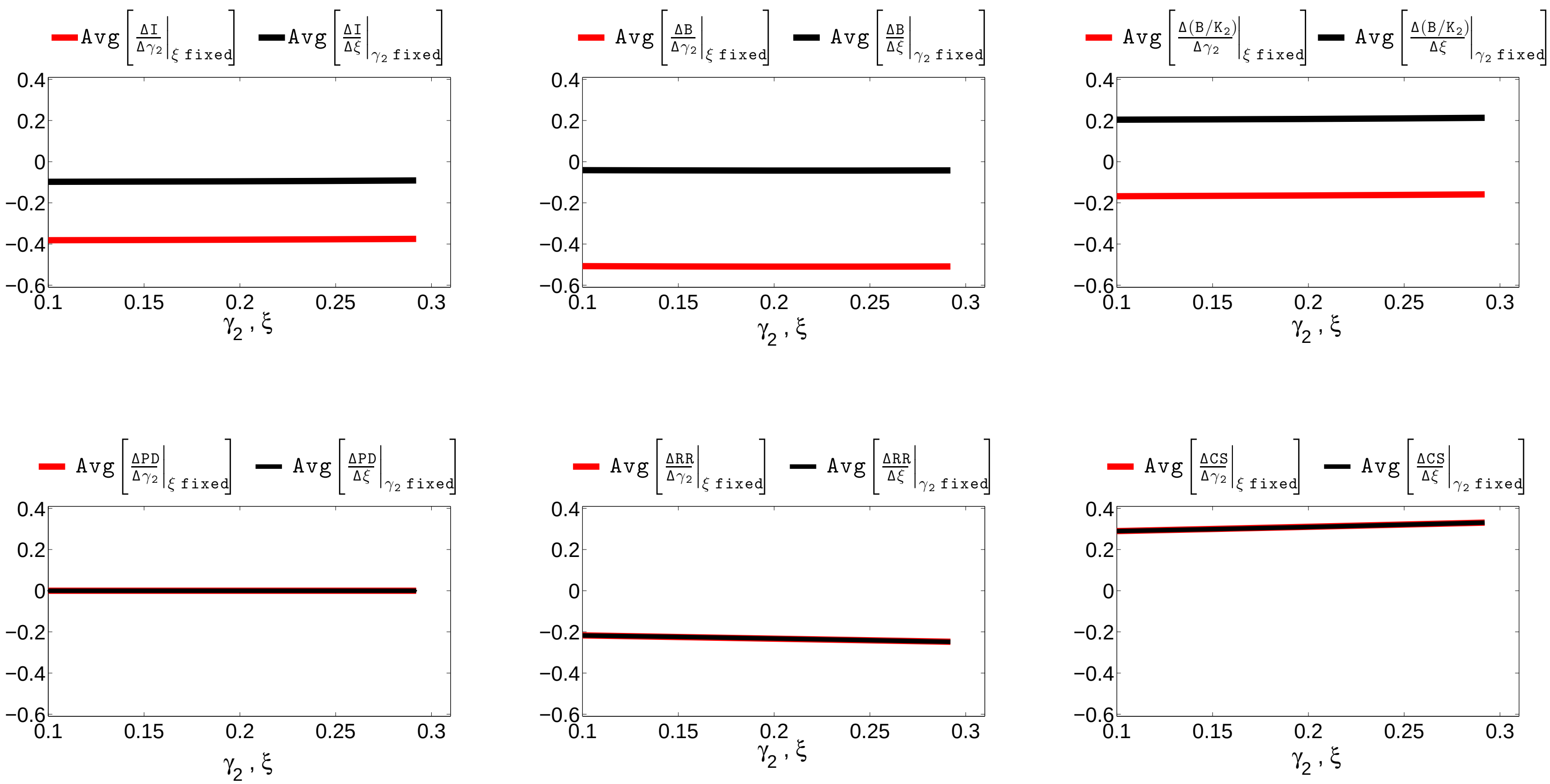
Aggregate impulse-response functions. This figure plots the impulse-response function to a positive long-run (black solid) and short-run (red dashed) productivity shock for productivity growth (Δx), investment growth (Δi), the aggregate debt and equity payout, the aggregate Market to Book ratio, the aggregate stock market excess return ($r_e - r_f$), the aggregate default probability (Default), the aggregate credit spreads (cs), and the inverse of aggregate maturity. The plots are calculated as deviation from the steady state. Units, when applicable, are specified next to the plot title.

Figure 2.2: Asset redeployability impulse-response functions



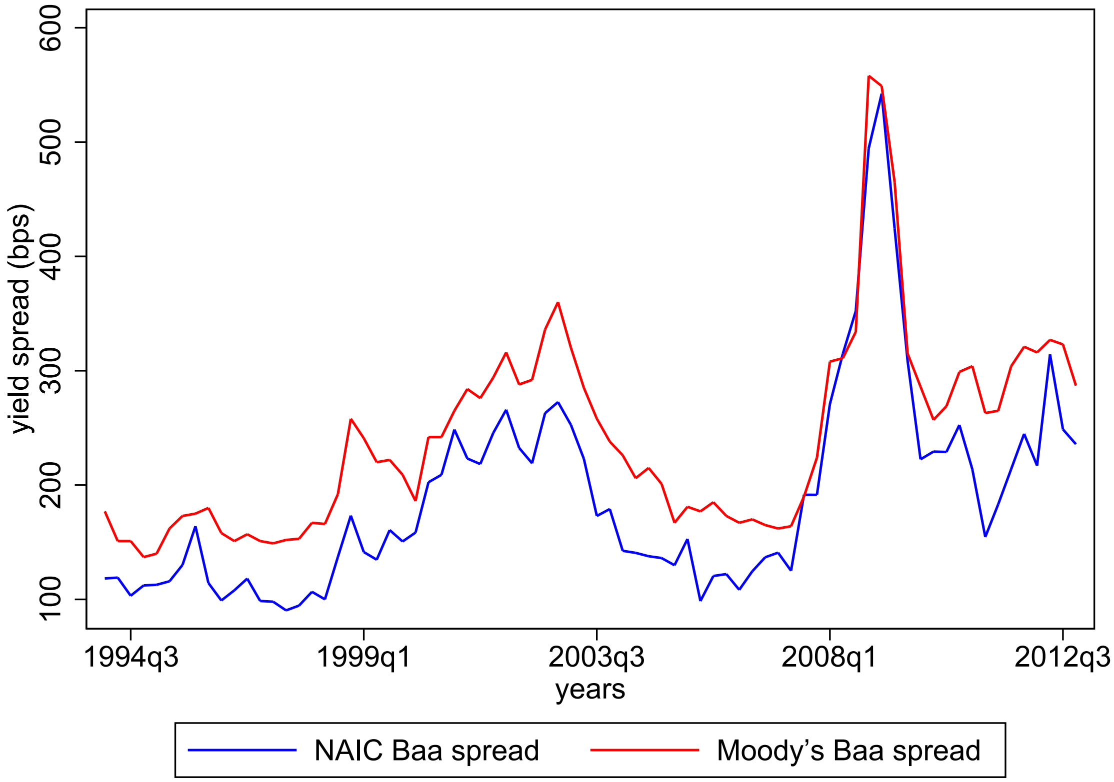
Asset redeployability impulse-response functions. This figure plots the impulse-response functions to a positive long-run productivity shock for industries that differ in their degree of asset redeployability. The responses in the low asset redeployability are plotted in red solid while those in the high asset redeployability are plotted in black solid. Each variable is described in Figure 2.1. The plots are calculated as deviation from the steady state. Units, when applicable, are specified next to the plot title.

Figure 2.3: Simple model's solutions



Simple model's solutions. The graph shows investment (I_1), leverage ratio (B/K_1), expected recovery rates (χ), and credit spreads ($cs = B/P(K_1, B) - 1$) resulted from solving the simple model for different values of investment irreversibility γ_2 and bankruptcy losses ξ. The grid of γ_2 and ξ are identical. The black line represents the difference between the variable obtained with the highest value of ξ and the lowest ξ keeping γ_2 constant. The red line represents the difference between the variable obtained with the highest value of γ_2 and the lowest γ_2 keeping ξ constant. To construct the graphs we set, $X_1 = 0.5$, $\mu = 0$, $\sigma = 0.6$, $\alpha = 0.4$, $\phi = 0.1$, $\psi_f = 0.1$, $f = 0.25$, $K_0 = 1e^{-3}$, $\gamma_1 = 0.02$, and ε is modeled as a discrete-state space with three states. In most of the solutions, the firm chooses to invest at the highest value of ε_2; whereas the firm prefers to disinvest at the mid and lowest value of ε_2.

Figure 2.4: Time-series of baa spreads



Time-series of Baa spreads from NAIC sample and Moody's. This figure compares the quarterly time series of average Baa bond spreads reported by Moody's and the same series constructed from the NAIC bond transaction file between 1994 and 2012. Yield spreads are in basis points. Bonds from NAIC are in U.S. dollars and have no special features (call, put, convertibility, etc.).

Chapter 3

Cyclical Distribution of Debt Financing

3.1 Introduction

Recent research has documented that the cross-sectional dispersion of *investment rate* comoves with the business cycle (Bachmann and Bayer (2014)). The authors argue that this procyclical behavior is a result of lumpy investment at the micro level.[1] Intuitively, a non-convex real cost that induces large and infrequent adjustments of the capital stock on a significant fraction of firms in good times can have a stronger effect on shaping the cross-sectional investment rate distribution than a countercyclical uncertainty shock.[2] In this chapter, I extend the result of Bachmann and Bayer (2014) to the cross-sectional debt issuance distribution. Specifically, I show that —as the cross-sectional dispersion of investment rate —the cross-sectional dispersion of *debt issuance* is also significantly procyclical.[3] Moreover, I build a DSGE model featuring heterogenous firms that show investment and debt issuance lumpiness to investigate the economic contribution of non-convex real and financing frictions.

To understand the sources of the procyclicality exhibited by the cross-sectional dispersion of the debt issuance distribution, I start documenting its significant positive correlation with measures of the extensive margin of firms' debt issuance and investment; namely, the fraction of firms undertaking large positive adjustments to either their stock of debt, capital or both.[4] To the extent that these groups of firms are potentially affected by different non-convex rigidities, I claim that the sources inducing lumpiness on firms' debt issuance and investment decisions have also the ability to shape the time-series dynamic of the cross-sectional dispersion of the debt issuance distribution. Then, to further investigate the economic determinants of the firm-level procyclical dispersion of debt issuance, I

[1]Gourio and Kashyap (2007) show that part of the aggregate investment can also be explained by investment lumpiness.

[2]The role of non-convex costs on shaping the distribution of investment rates has also been studied by Doms and Dunne (1998), Caballero et al. (1995), Cooper and Haltiwanger (2006), Bachmann et al. (2013) and Bachmann and Bayer (2014).

[3]As described in details in Section 3.2, debt issuance is defined as the change of total debt (sum of short- and long-term) scaled by total assets as in Salomao et al. (2014) and Covas and Den Haan (2011, 2012).

[4]As Bachmann and Bayer (2014), large positive (negative) adjustment of the capital stock —i.e. *investment spikes* —are defined as investment rates higher (lower) than 5% (-5%) of total assets. Large positive (negative) adjustments of the debt stock —i.e. *debt issuance spikes* —are defined as debt issuance higher (lower) than 5% (-5%) of total assets.

build a structural model of heterogeneous firms facing non-convex real and financing costs.

The model shows that a non-convex real rigidity is not sufficient to cause a procyclical dispersion of the cross-sectional distribution of debt issuance. In short, within the model, investment lumpiness does not produce enough debt issuance lumpiness. Consequently, investment lumpiness by itself cannot reproduce the time-series dynamic showed by the firm-level debt issuance distribution in the data. Intuitively, even if capital adjustments are large and infrequent, in the absence of a non-convex debt adjustment cost firms will tend to adjust their debt stock too smoothly; only responding to changes of the tax-benefit of debt and/or the risk of bankruptcy cost. In the model, the tax-benefit of debt and the risk of bankruptcy cost are mainly driven by a firm's profitability which in the simulations does not exhibit extreme adjustments. Thus, after calibrating the model to a series of aggregate and cross-sectional moments, I discuss and quantify the contribution of both non-convex cost of capital and debt adjustment on shaping the business cycle properties of firm-level investment and debt issuance decisions.

This chapter makes three contributions. First, I complement existing works studying the time-series properties of aggregate debt financing (Jermann and Quadrini (2009)) by showing that in the cross-section, the dispersion of the firm-level distribution of debt issuance also shows a significant positive correlation with the business cycle. This finding highlights the fact that looking at aggregate variables can mislead our comprehension of firms decisions. Second, I add to the analysis undertaken by Bachmann and Bayer (2014) of the cross-sectional distribution of investment rate by investigating the economic mechanism leading to a procyclical dispersion of the cross-sectional distribution of debt issuance. The analysis conducted in this chapter provides evidence regarding an important implication of micro-decisions that a model featuring heterogenous firms undertaking investment and financial decision should consider to account for. Lastly, I complement the study conducted by Bazdresch (2005) regarding the role played by large and infrequent changes of firms' debt stock on shaping the cross-sectional distribution of debt issuance. Bazdresch (2005) focus on studying the average asymmetry of the firm-level debt issuance distribution. In this chapter, I use Bazdresch (2005)'s premise to show that non-convex rigidities affecting both capital and debt adjustments in addition to a countercyclical price of risk induce a cyclical dynamic not only on the cross-sectional average of the debt issuance distribution but also on its second moment.

In the empirical motivating section of this chapter, I start showing that the cross-sectional distribution of debt issuance is indeed positive skewed on average; i.e. reproducing Bazdresch (2005) results. The average coefficient of the asymmetry of the distribution—quantified by a skewness coefficient of about 3.4 —, appears to be shaped by large and positive adjustments of the debt stock.[5] Indeed, the average fraction of firms exhibiting positive large debt issuance spikes from 1984 and 2016 is about 8.1%; whereas the average fraction of firms exhibiting negative large debt issuance spikes in

[5] Refer to footnote 4 in this chapter for a detailed definition of —positive and negative —investment and debt issuance spikes used throughout tables.

the period studied is lower in magnitude, i.e. 5.9%.[6]

Next, I proceed to explore further these periods of large adjustments of the debt stock in the data by studying their relation to aggregate variables. In particular, I continue showing that both positive and negative large adjustment of debt stock correlates positively (0.61) and negatively (-0.42) with the business cycle,[7] respectively. That is, despite that there are some firms adjusting strongly their debt stock in response to various shocks, these large responses seem to be stronger in good times of the economy. Furthermore, I show that the strong link with the business cycle exhibited by the fraction of firms showing positive debt issuance spikes induces a cyclical time-series dynamic on the dispersion of the cross-sectional distribution of debt issuance; which is quantified by a correlation with the business cycle of about 0.43. Indeed, the cross-sectional dispersion of debt issuance appears to be closely related to positive debt issuance spikes. The time-series correlation between both variables in the sample is positive and significant (0.85).[8]

Interestingly, the data also suggests that the procyclicality of the dispersion of the debt issuance distribution does depend on both real and financial frictions. From the first quarter of 1984 to the last quarter of 2016, the correlations of the cross-sectional dispersion of the debt issuance distribution with the fraction of firms showing either positive debt issuance spikes, positive investment spikes or both simultaneously, result significant and positive. Then, to the extent that these different groups of firms undertaking large adjustments of capital and/or debt are affected differently on the margin by real and financial rigidities, these findings reveal that the features of the cross-sectional dispersion of debt issuance distribution do depend on a combination of real and financial frictions.[9]

I use this result to further explore the economic mechanisms behind the procyclicality of the firm-level debt issuance in terms of its cross-sectional dispersion. The second building block of this chapter is based on a quantitative model of heterogenous firms that allows me to study the importance of non-convex costs of capital and debt adjustment on shaping the firm-level distributions. To accomplish this goal, I conduct several comparative statics in terms of the real and financial non-convex costs. The main objective is to quantify the contribution of both rigidities on determining the distribution of debt issuance and investment rate in terms of their (i) coefficient of asymmetry (skewness), (ii) time-series correlation with the business cycle exhibited by the fraction of firms showing large positive adjustments (spikes), and; (iii) time-series correlation with the business cycle exhibited by the both cross-sectional dispersion. Broadly, the model predicts that a combination of both real and debt issuance rigidities are required to reproduce the empirical behavior of the firm-level distribution of debt issuance described before.

[6]Refer to Table 3.1, Panel A for more details regarding these results.

[7]Real output is measured by real GDP (in local currency at constant prices) and its cyclical component is obtained by detrending the time-series using the band-pass (BP) filter due to Baxter and King (1999).

[8]In contrast, the correlation of the cross-sectional dispersion of debt issuance with the fraction of firms exhibiting negative debt issuance spikes in the sample is slightly significant (-0.22). Note that, as discussed by Bachmann and Bayer (2014) for the investment rate distribution, the correlation of the cross-sectional dispersion of investment rate with the fraction of firms exhibiting positive investment spikes in the sample is highly significant (0.94).

[9]Table 3.1 provides more details about these results. Footnote 4 gives definitions of investment and debt issuance spikes.

Indeed, in the model, low values of the non-convex cost of capital adjustment reduces not only the asymmetry on the cross-sectional investment rate but also makes the cross-sectional debt issuance distribution more symmetric. Intuitively, in the context of countercyclical aggregate uncertainty and more flexible (dis)investment, positive adjustments of capital stock in good times are as frequent as negative adjustments of capital stock in bad times; that is, the overall asymmetry of the cross-sectional distribution of investment rates decreases in this context. Within the model, aspects of the firms investment decisions are also reflected on firms' financial needs. Then, in the presence of difficulties for obtaining equity financing,[10] debt issuance distribution becomes more symmetric since patterns of investment decisions will also affect debt issuance decisions. Effectively, when firms do not show large financial needs, adjustment of the stock of debt will tend to be frequent and small balancing both the tax-benefit of debt and the risk of bankruptcy cost. As discussed by Bazdresch (2005), in this case debt adjustments are mainly determined by changes in firms' profitability; which, under careful modeling of the idiosyncratic productivity shocks,[11] will not show extreme variations from period to period. Consequently, when real non-convex cost are small, the drivers of the time-series dynamic of the cross-sectional dispersion of investment rate and debt issuance will not be strong enough to induce procyclicality on both dispersions. In fact, in this case, the cross-sectional dispersion of both firms' variables will end up reflecting more the business cycle properties of the underlying idiosyncratic productivity shock which in the model follows an heteroskedastic process with countercyclical volatility (as in Bloom (2009), and Bachmann and Bayer (2014); among others).

In contrast, a high non-convex real cost renders large adjustment of the capital and debt stock not only more likely but concentrated in booms. This behavior of positive investment and debt issuance spikes induces a more procyclical behavior on the cross-sectional dispersion of both distributions investment rate and debt issuance. Within the model, a high non-convex real friction reduces the firms' incentive to scale down capital in response to a higher dispersion of the idiosyncratic shocks at recessions when the price of risk is sizable. Intuitively, in the presence of high non-convex real friction, in recession the value of the option to disinvest is not high enough to offset the fixed cost associated to this decision. On the other hand, in the model, large adjustment of the capital stock becomes relatively more frequent in good times due to a real option effect. Indeed, in good times, firms decide to adjust their capital stock by paying the fixed adjustment cost since their risk become lower due to both lower dispersion of the idiosyncratic technology shock in conjunction with a lower price of risk. Then, in this case, due to large financial needs faced in booms and in the presence of rigidities on issuing equity, firms will also tend to exhibit large debt adjustments in good times. As a consequence, an increase on the non-convex real cost in the model leads to an increase of the procyclicality of the cross-sectional dispersion of both debt issuance and investment rates.

[10] In the model, firms also face difficulties for obtaining equity financing which are calibrated to match the aggregate frequency of equity issuance, as described in Section 3.4.

[11] As described in Section 3.3, idiosyncratic productivity shocks are modeled as a persistent process implemented using a grid containing enough points to avoid dramatic changes in firms' profitability.

Simulations from the quantitative model reveals that some degree of the non-convex debt issuance cost is required to reproduce the business cycle dynamics of the cross-sectional dispersion of debt issuance. When the fixed cost of issuing debt is low, firms tend to adjust their debt position too frequently. Indeed, as mentioned above even in the presence of non-convex costs of capital adjustment, firms adjust optimally their debt stock every period in order to balance the tax benefit of debt and the costs associated to bankruptcy risks. In the context of countercyclical aggregate uncertainty, a low value of the non-convex real cost will not only reduce large adjustment of the stock of debt; but also negative adjustments will be as frequent as positive adjustments. This behavior will lead to a less procyclical cross-sectional dispersion of the debt issuance distribution. Furthermore, when debt financing does not involve important additional costs, changes in capital will become more frequent and thus large investment lumps will be less likely to observe and will also resemble the evolution of the aggregate uncertainty. Overall, low fixed cost of issuing debt will lead to a more symmetric distribution of investment rate and debt issuance. And, it will also imply a less procyclical cross-sectional dispersion of the debt issuance distribution.

In contrast, increasing the fixed cost of issuing debt makes debt adjustment less frequent, large and significantly linked to firms' financial needs. Consequently, in the presence of countercyclical price of risk and countercyclical dispersion of idiosyncratic shocks, high levels of non-convex debt issuance and investment cost render debt adjustment spikes more likely to be observed in good times and therefore; the cross-sectional dispersion of debt issuance distribution in this case becomes more correlated with the business cycle.

Specifically, to quantitatively assess the importance of non-convex costs of capital and debt adjustments on shaping the firm-level distributions of debt issuance and investment, I start calibrating the quantitative model to match a broad set of aggregate and cross-sectional moments. Importantly, in the model, differences along idiosyncratic technology shocks are the only difference across firms.[12] Using the model, I find that both non-convex rigidities linked to debt issuance and investment lumpiness are key to match procyclical behavior of the cross-sectional dispersion of debt issuance and investment rate. The benchmark calibration produces a large significant correlation of these cross-sectional moments with the aggregate output (0.49 and 0.45, respectively). Note that these values are in line with their empirical counterparts I obtained from the CRSP/Compustat Merged (CCM) Fundamentals Quarterly file (0.56 and 0.43, respectively).[13]

In the next section, I provide a discussion about how this chapter fits and contributes to the existing literature on corporate finance that studies the link of firms' decisions to aggregate economic shocks.

[12]As in Bloom (2009), Bachmann and Bayer (2014), idiosyncratic technology shocks are modeled as a heteroskedastic process with time-varying transition matrices between idiosyncratic productivity states, where the matrices correspond to different values of the technology shock dispersion.

[13]Refer to Table 3.1, Panel A for more details regarding these results.

3.1.1 Literature review

I contribute to the literature on corporate finance that studies the response of firms' investment and financing decisions to changing economic conditions by studying higher-order moments of the firm-level debt issuance distribution.

Influential works by Kiyotaki and Moore (1997), Bernanke et al. (1999), Caballero (1999), Gourio and Kashyap (2007), Jermann and Quadrini (2009), Khan and Thomas (2011), and Khan et al. (2014) use structural models of default with financial frictions to study cyclical fluctuations of aggregate financing in response to aggregate shocks. The general consensus is that financial frictions exacerbate the negative effect of economic recessions. I add to this discussion by pointing out that, despite that on average debt issuance increases in good times, firms respond differently to good aggregate shocks. Specifically, I claim that these distinct behaviors ultimately affect other (higher-order) moments of the cross-sectional distribution of debt issuance.

At the firm-level, the corporate finance literature has showed that firms' response to aggregate shocks in terms of their financing decisions depend on other firms' characteristics. For instance, Covas and Den Haan (2011, 2012), and Salomao et al. (2014) show that, unlike large firms, small firms do not substitute equity by debt financing over the business cycle. They argue that since the cost of debt of small firms increases importantly in bad times, small firms' ability to fund their financial needs by issuing debt is importantly reduced in recessions. Similarly, Korajczyk and Levy (2003) discuss to what extent negative macroeconomic conditions affect the capital structure decision of financially unconstrained firms, but have little impact on financially constrained firms. In this chapter, I build on this literature by showing empirically that the distinct response of firms to aggregate shocks —in terms of their debt issuance decision —induces business cycle dynamics not only on the aggregate debt issuances, but also on the dispersion of its cross-sectional distribution. Indeed, using a quantitative model, I claim that this dynamic of the cross-sectional dispersion of debt issuance depends mainly on the underlying firms' ability to costlessly adjust their debt stock over time.

Previous research has also studied the effect of firms' financial rigidities on their investment decisions. In a model where firms face fixed debt issuance costs, Cummins and Nyman (2004) argue that financial non-convexities help to understand why firms in the data hold external finance and idle cash simultaneously. Gomes (2001) construct a general equilibrium model of investment and financing and show that even in the presence of financial constraints, Tobin's Q is a sufficient statistic to explain firms' investment. Cooper and Ejarque (2001) show that firms' financial constraints are not necessary to obtain a strong relationship between investment and profits. In contrast to some of these works, in this chapter I show that non-convex financial cost are key to match the empirical business cycle dynamic of the firm-level debt issuance and investment rate distribution. Particularly, in this chapter, I propose large infrequent change in debt and investment stock as an important source of these time-series properties.

The investment literature has extensively highlighted the role played by non-convex costs of capital adjustment on shaping the firm-level investment rate distribution (Abel and Eberly (1996), Caballero and Engel (1999), Bachmann and Bayer (2014), among others). As in Bazdresch (2005), in this chapter I also emphasize the importance of non-convex costs of debt adjustment to shape the business cycle dynamic exhibited by the entire cross-sectional distribution of debt issuance. Furthermore, I discuss the interaction between real and financial non-convexities which I use to rationalize the empirical motivating results presented in the introductory section and discussed in details in Section 3.2. Recent empirical work points out that firms' capital adjustment decisions are importantly affected by the corporate bond market. In addition to the tight link between credit spreads and aggregate investment growth suggested by Lettau and Ludvigson (2002), Philippon (2009) shows that a bond-market-based Q can explain an important part of the variation of aggregate investments.[14] The aim of this chapter is to contribute to this discussion by showing that both investment as well as debt issuance lumpiness are required to reproduce empirical correlations of different moments of the firm-level distribution of debt issuance with the business cycle.

More broadly, in this chapter I exploit the high degree of heterogeneity that firms' debt issuance decisions exhibit in the cross-section (Bazdresch (2005)) in conjunction with their link to the business cycle to assess the importance of commonly financial frictions used in the literature to understand firms' financing decisions. Specifically, I target the asymmetry exhibited by firms' debt issuance and investment decisions in the cross-section to discipline an otherwise standard DSGE model with heterogenous firms facing investment and financing decisions in order to reproduce the business cycle dynamic exhibited by the cross-sectional dispersion of debt issuance and investment rate distribution.

The rest of the chapter is organized as follows. Section 3.2 presents several empirical results that motivate this work. Section 3.3 develops a DSGE model featuring heterogenous firms that I use to study the importance of non-convex costs of capital and debt adjustment on shaping the cross-sectional distributions of debt issuance and investment. Section 3.4 discusses the baseline calibration. Section 3.5 investigates some of the model's quantitative implications for the cross-section of investment rate and debt issuance that is followed by a few concluding remarks in Section 3.6.

3.2 Empirical analysis

In this section, I start describing the database used to compute the results that motivate this chapter. Next, I provide empirical evidence showing that large *positive* adjustments of firms' debt stock not only explain the average asymmetry exhibited by the cross-sectional distribution debt issuance, but also induce its dispersion to *comove* with the business cycle. Business cycle is defined as the cyclical component of real GDP growth obtained by detrending real GDP growth time-series using a band-pass (BP) filter (Baxter and King (1999)). Lastly, I complement the previous finding by documenting that large *positive* adjustments of capital stock also contribute to the cyclical pattern of the cross-

[14]Recently, Yamarthy et al. (2015) examine the role of financial frictions in determining firms' investment decisions. Yamarthy et al. (2015) argue that the effect of contracting friction on firms' real decisions is much weaker relative to a standard convex adjustment cost.

sectional dispersion of the debt issuance distribution. Using these findings, I conclude motivating the study of the effect of debt issuance and investment lumpiness on the cross-sectional debt issuance distribution conducted in Section 3.3.

3.2.1 Data and variable description

The empirical part of this chapter is based on the CRSP/Compustat Merged (CCM) Fundamentals Quarterly file. In order to be consistent with the quantitative business cycle literature, I work with data from the first quarter of 1984 to the last quarter of 2016. In the empirical analysis, I also use data on real quarterly GDP and the price level from NIPA tables.

Next, I describe the data treatment applied to the original CCM Fundamentals Quarterly database. As standard in the corporate finance literature, I start dropping financing firms (SIC codes 6000-6999), regulated utilities (SIC codes 4800-4999), and non-profit firms (SIC code 9000-9999). For the results of this section, I do not consider the information of the first year a firm appears in the database to eliminate any IPO effect. Following Salomao et al. (2014), I also drop firms where total assets are zero or missing. Firms where the accounting identity is violated by more than 10% of total assets are discarded. Observations where leverage ratio is larger than the unity are eliminated as well as observations of those firms that where recorded in the database less than one year.[15] These filters leave a sample of 363,512 firm-quarter observations from 11,236 different firms. On average, a firm is observed in the sample for 32 quarters. The average number of firms in the cross-section of any given year is 3,195. The resulting sample covers roughly 43 percent of the original sample.[16]

In what follows, I describe the definitions of the variables used in the empirical analysis; which follow closely Salomao et al. (2014). In the analysis, debt issuance are defined as the change of total debt stock; where total debt stock is defined as the sum of long- and short-term debt. From the definitions of the CCM database, long-term debt comprises debt obligations that are due more than one year from the company's balance sheet date; where debt obligations include long-term lease obligations, industrial revenue bonds, advances to finance construction, loans on insurance policies, and all obligations that require interest payments. Short-term debt is defined as the sum of long-term debt due in one year and short-term borrowings. In the analysis conducted, I work with debt issuance scaled by total assets. I compute total assets as the average of last three years assets adjusted by the price level. I choose this definition of total assets to obtain most of the variation of the ratio from debt issuances.[17] In terms of the investment rate, I follow the literature on investment and define a firm's investment rates as the firm's capital expenditures scale by total assets.

In the next section, I start studying the average properties of the cross-sectional distribution of

[15] Filters applied to the CCM Fundamentals Quarterly database are very similar to those applied in Colla et al. (2013).

[16] In the Appendix B.1, I show that the empirical results presented in this section also remain robust to the exclusion of small firms. To assess the importance of small firms in the results, I conduct the same analysis by excluding firms with total asset lower than $10,000. Table B.1 shows that business cycle dynamics of the cross-sectional distribution of debt issuance and investment reported in Table 3.1 remain quantitatively unchanged.

[17] Similarly, Salomao et al. (2014) scale debt issuance by the firm's total asset trend.

debt issuance following the analysis conducted for the firm-level investment rate by Caballero et al. (1995), Bazdresch (2005), and Bachmann and Bayer (2014). The main goal is to show that the debt issuance cross-sectional distribution is affected importantly by large positive adjustments determining its average asymmetry. After this analysis, in the following section, I proceed to link the cyclical features of large positive adjustments of the debt stock to the cyclical pattern showed by the dispersion of the debt issuance firm-level distribution.

3.2.2 Debt issuance lumpiness

The purpose of this section is to study some features of the debt issuance cross-sectional distribution. While I show that the debt issuance cross-sectional distribution is importantly affected by large adjustments of the debt stock (as in Bazdresch (2005));[18] I add to these findings by showing that the positive large adjustments of the debt stock have a stronger effect on the cross-sectional debt issuance distribution which is reflected not only on its average asymmetry but also its business cycle properties.

As a starting point, I proceed to compare the observed firm-level debt issuance distribution to its normally simulated counterpart. As in Bazdresch (2005), for each firm that exhibits continuous quarterly observations over the sample period 1984Q1-2016Q4, I proceed following the next steps. First, I rank the firm's quarterly debt issuance from the highest to the lowest debt issuance into bins.[19] Next, I compute the simulated debt-issuance counterparts of the firm for each bin. Specifically, I assume the simulated variable comes from a normal distribution with mean and standard deviation given by the sample mean and standard deviation of the firm's quarterly debt issuance ratios. Then, the simulated debt issuance ratio ($x_{j,i}$) of firm j-th associated to bin $i \in [1, N_b]$ corresponds to the solution of the equation $\Phi_j(x_{j,i}) = {}^{i}/_{N_b}$; where Φ_j represents the cumulative density function of a normal distribution with mean and standard deviation equal to the sample mean and standard deviation of firm j-th quarterly debt issuance. After repeating the exercise for each firm, I construct the averages over all firms by bin.

Figure 3.1 shows, in red bars, the sample average debt issuance over all firms by bins. Note that by construction bars are decreasing (on average). Figure 3.1 also presents, in blue line, the average by bin that resulted from the simulated debt issuance ratios ($x_{j,i}$). As can be observed in Figure 3.1, a small number of periods account for most of the debt issuance action across firms. Unlike to the simulated debt issuance (blue line), extreme values of the observed debt issuance (red bars) are much larger compared to the values in the middle of the distribution. In fact, on average, while 85% of the firm-quarter observations shows a debt issuance lower than 3% of the firm's total assets; only 5% of the firm-quarter observations accounts for 52% of the firm's total (positive) debt issuance in the

[18] The importance of large adjustments on shaping the distribution of firm-level decisions has also been documented for investment rates (Doms and Dunne (1998), Caballero et al. (1995), Cooper and Haltiwanger (2006), Bachmann et al. (2013) and Bachmann and Bayer (2014)).

[19] Since this exercise uses firms that exhibit continuous quarterly observations from the first quarter of 1984 to the last quarter of 2016, the total number of bins used is $4 \times (2016 - 1984 + 1)$.

data. The corresponding numbers for the simulated debt issuances (blue line) are 66% of the firm-quarter observations being below 3% of the firm's total assets; and 5% of the firm-quarter observations accounting for only 24% of the firm's total (positive).

Following Bazdresch (2005) definition of a debt-issuance inaction period, I proceed to define a large positive (negative) debt issuance *spike* as a change in debt issuance higher (lower) than 5% (-5%) of the firm's total assets.[20] Table 3.1 Panel A first columns reports the average fraction of firms with positive $(+)$ and negative $(-)$ debt issuance spikes per period. While the average fraction of firms with positive debt issuance spike is 8.1%, the average fraction of firms with negative debt issuance spike is only 5.9%. This difference between positive and negative large adjustments of debt issuance induces asymmetry on the debt issuance distribution as can be observed in its average positive skewness (3.4) exhibited on Figure 3.1. Note that the simulated debt issuance distribution in Figure 3.1 —which does not present important differences between positive and negative spikes by construction —shows a coefficient of asymmetry of only 0.14.

Furthermore, as evidenced by Figure 3.4,[21] the difference between the fraction of firms with positive debt issuance spike and the fraction of firms with negative debt issuance spike seems to increase in good time and decrease in recessions. Indeed, as reported in Table 3.1 Panel A second column, while the fraction of firms with positive debt issuance spike correlates positively with the business cycle (0.61); the fraction of firms with negative debt issuance spike shows a negative correlation with the business cycle (-0.42). As illustrated by Figure 3.4, during recessions large positive debt issuance spikes decreases dramatically. For instance, during the last two financial crisis the fraction of firms exhibiting positive debt issuance spikes falls by almost half. It is noteworthy to mention that the relative importance and procyclicality of large positive spikes can also be observed in the cross-sectional distribution of investment rates as reported by Table 3.1 Panel A last two columns.[22]

In the next section, I describe the implications of the behavior of positive debt issuance spikes as well as investment spikes on the time-series dynamic of the cross-sectional distribution of debt issuance.

3.2.3 Implication of debt issuance lumpiness

In this section I start showing that the relative importance and procyclicality exhibited by the positive debt issuance spikes induce a procyclical behavior on the cross-sectional dispersion of the debt

[20] For annual investment rates, Cooper and Haltiwanger (2006), Gourio and Kashyap (2007) and Bachmann and Bayer (2014) define spikes as cases where investment relative to the beginning of period capital is greater than 20 percent. Since I base my results on quarterly data I choose 5%. Moreover, in the CCM quarterly database, firms with debt issuance larger than 5% (lower than -5%) correspond to firms in the top (bottom) decile of the average debt issuance distribution.

[21] In this section, while seasonally smoothed variables are used to construct time-series pictures; correlation statistics are computed using variables resulted from applying a band-pass filter to the deflated original variable. In this aspect of the analysis, I followed closely Salomao et al. (2014).

[22] The correlation of the fraction of firms exhibiting positive investment spikes with the business cycle is positive and significant (0.59). Whereas, the correlation of the fraction of firms exhibiting negative investment spikes with the business cycle is not statistically significantly different from zero.

issuance distribution. Next, I document a similar result for the cross-sectional dispersion of the investment rates distribution; i.e. highlighting the role of high and procyclical positive investment spikes on shaping the dynamic of the investment rate cross-sectional distribution.[23] Finally, I show suggestive evidence regarding the importance of the interaction between positive debt issuance and investment spikes on the business cycle dynamics of the cross-sectional distribution of debt issuance.

I start describing the positive correlation of the cross-sectional dispersion of the debt issuance distribution with the business cycle.[24] Table 3.1 Panel A reports that this correlation is significant and equal to 0.43. Figure 3.3, blue line, illustrate the procyclicality of the cross-sectional dispersion of the debt issuance distribution. To my knowledge, this property has not been previously documented and explored in the literature. Table 3.1 Panel B shows suggestive evidence about the importance of positive debt issuance spikes on shaping the cross-sectional dispersion of the debt issuance distribution. In fact, the correlation between the fraction of firms with positive debt issuance spikes and the cross-sectional dispersion of the debt issuance distribution is significant and equal to 0.85. Note that the importance of positive large adjustments on shaping the cross-sectional distribution is also present in the investment rate distribution. Table 3.1 shows that the cross-sectional dispersion of the investment rate distribution is highly procyclical; and furthermore, its correlation with the fraction of firms with positive investment spikes is significant and equal to 0.94.

Intuitively, these findings suggest that the procyclicality showed by the cross-sectional dispersion of debt issuance as well as investment rates is driven by an important increase of the right tail of the distribution in good times. Knowing this feature of the cross-sectional distribution of firms' decisions can be important for understanding the procyclical behavior of aggregate variables. In fact, as pointed out by Gourio and Kashyap (2007) for aggregate investment, the results in Table 3.1 Panel B suggest that the variation in aggregate debt issuance depends mainly on a small fraction of firms undergoing debt issuance spikes in good times. It is noteworthy that although recent works in corporate finance have focused on analyzing the implicit information in other moments of the debt issuance distributions (e.g. Bazdresch (2005)), still we know little about its time-series properties. This chapter intends to add to this area.

Table 3.1 Panel B shows that a potential driver of the procyclical dispersion of debt issuance distribution is a set of firms showing a dramatic increase of their debt stock —i.e. debt issuance lumpiness. In reality, debt issuance lumpiness can occur in response of either in response to financial non-convex frictions that hamper the adjustment of the debt stock or/and investment lumpiness. Recent literature on corporate finance highlights the role played by real and financial non-convexities on shaping the *average* asymmetry of the debt issuance cross-sectional distribution. More broadly, frictions of different types will be affecting simultaneously multiple firms' decisions. Table 3.1 Panel

[23] Bachmann and Bayer (2014) present a similar results using a panel of German firms with annual observation from 1973 to 1998. The authors' primary data source is the Deutsche Bundesbank balance-sheet database, USTAN.

[24] Business cycle corresponds to a band-pass (BP) filter of real GDP (in local currency at constant prices) using the methodology proposed by Baxter and King (1999).

C intends to provide evidence about this interaction.

To understand the economic mechanism behind the procyclicality of the cross-sectional dispersion of the debt issuance distribution, Table 3.1 Panel C (second column) reports its correlation with various types of firms potentially affected by non-convex rigidities; that is, firms likely experiencing debt issuance and/or investment lumpiness. For instance, since firms showing positive debt issuance spikes (Panel C, first row) can be facing both real and financial non-convex costs simultaneously, I also present correlations with the group firms experiencing debt issuance lumpiness but not investment lumpiness (Panel C, third row). In fact, within this last group, while firms are increasing the debt stock importantly; they adjust their capital stock marginally. Similarly, I study the correlations of the cross-sectional dispersion with those firms showing investment lumpiness (Panel C, second row) as well as with those firms experiencing investment lumpiness but not important changes in the stock of debt (Panel C, fourth row). Results reported in Table 3.1 Panel C show that the evolution of the number of firms in each group exhibits a positive significant correlation with the cross-sectional dispersion of both debt issuance and investment distribution. Furthermore, as evidenced in Figure 3.5, the fraction of firms within these groups experiencing either debt issuance lumpiness or investment lumpiness varies importantly over time.

In the next section, I use these findings to argue that both real and financial non-convex rigidities can affect the cross-sectional dynamics of the debt issuance as well as investment rate distribution and therefore, the cross-sectional dispersion of debt issuance is not just a reflection of the properties showed by the cross-sectional dispersion of investment rate (Bachmann and Bayer (2014)). Thus, the objective of pursuing a quantitative model in this chapter is to quantify the contribution of these two type of non-convex rigidities on driving the dynamic of the cross-sectional dispersion of the debt issuance distribution. Specifically, to accomplish this quantitative analysis in Section 3.3, I develop a structural general equilibrium model of heterogeneous firms featuring both lumpy investment and debt financing decisions.

3.3 Benchmark model

In this section, I describe the dynamic stochastic general equilibrium model used in this chapter to explain the empirical motivating facts regarding the cross-sectional distribution of debt issuance. In the model, time is discrete and firms' horizon is infinite. The economy consists of a distribution of value-maximizing, each able to produce a homogeneous good and owned by risk-averse investors. Firms make investment, hiring and financing decisions given the stochastic discount factor derived from the representative household's problem in a general equilibrium setting. Firms' external financing sources consist of equity and non-contingent long-term debt. As, in Khan et al. (2014), Firms issue non-contingent long-term debt to a perfectly competitive representative financial intermediary at loan rates determined by their individual characteristics.[25] Importantly, firms adjust capital and debt stock facing non-convex costs of capital and debt stock adjustment.

3.3.1 Firms

A cross-section of heterogenous firms make optimal investment and financing decisions by taking as given real and financing costs as well as the representative household stochastic discount factor that is derived from a representative household who has recursive preferences. Each period, a firm chooses its new capital stock (k_{t+1}) and how to finance these purchases with the goal of maximizing the present value of after-tax cash flows to shareholders. To finance its investment and shareholders' distributions at period t, a firm uses internal earnings, new debt issues and/or new equity issuance. In the model debt is long-term. As in Kuehn and Schmid (2014), at each period t, a firm can controls the book face value of debt outstanding b_{t+1}; and corporate bonds have a fixed coupon rate $c \in (0,1)$ and repay a constant fraction $\lambda \in (0,1)$ of the bond's face-value each period.

Production Technology

There is one homogenous commodity in the economy which can be consumed or invested. The j-th firm produces the homogenous commodity using capital $k_{j,t}$ and labor $l_{j,t}$ and subject to both an aggregate shock x_t and an idiosyncratic shock $z_{j,t}$; according to a Cobb-Douglas production function,

$$y_{j,t} = e^{x_t(1-\alpha)} e^{z_{j,t}} (k_{j,t})^{\alpha} (l_{j,t})^{1-\widehat{\alpha}}, \quad \text{with} \quad \alpha, \widehat{\alpha} > 0 \quad \text{and} \quad \alpha + \widehat{\alpha} < 1 \tag{3.1}$$

where x_t and $z_{j,t}$ are log aggregate and log idiosyncratic productivity shocks, respectively. The growth rate of the aggregate shock is modeled as a random walk with time-varying drift and volatility,

$$\Delta x_{t+1} = g + \mu_x(s_t) + \sigma_x(s_t)\varepsilon_t^x \tag{3.2}$$

where the low-frequency component in the aggregate productivity equation, $\mu_x(s_t)$ is used to generate sizeable risk premia whereas the time-varying volatility is useful to generate realistic credit spreads. The variable s_t is an aggregate variable taken as given by all firms each period to solve their maximization problem. The exogenous aggregate state (s_t) will be modeled as a persistent process through a Markov chain described in Section 3.2. The idiosyncratic log productivity process is modeled as a Markov process with autocorrelation ρ_z and time-varying conditional standard deviation, $\sigma(s_t) \equiv s_t + \bar{\sigma} > 0$. That is, firms can observe their idiosyncratic technology shock once the aggregate state of the economy s_t is revealed. In the solution used, I assume that shocks to the exogenous aggregate states, and idiosyncratic productivity shocks are independent. Further, idiosyncratic pro-

[25] Having the assumption of the existence of a financial intermediary participating in a competitive market facilitates the market clearing conditions in the definition of the recursive equilibrium. A complete characterization of the recursive equilibrium is provided in the Appendix B.2.3.

ductivity shocks are independent across productive firms. Using these definitions and assumptions, the flow of operating profits $\Pi_{j,t}$ of firm j at period t is given by,

$$\Pi_{j,t} = y_{j,t} - w_t \times l_{j,t} - f \times k_{j,t} \tag{3.3}$$

where the aggregate wage is denoted by w_t, and $f > 0$ represents a proportional cost of production. I use f to match the book leverage. In the economy, capital stock depreciates at the rate $\delta \in (0,1)$; but firms possess the option to adjust their capital stock by pursuing investment decisions.

Investment

The investment of firm j at period t, $(i_{j,t})$, required to change the capital stock to $k_{j,t+1}$ is defined by, $i_{j,t} \equiv k_{j,t+1} - (1-\delta)k_{j,t}$. Yet, each period, the firm j-th faces a non-convex cost $\Omega^k(i_{j,t})$ if its investment differs from zero. I model this cost as a deduction from firms' profits. Specifically,

$$\Omega^k(i_{j,t}) = \begin{cases} 0 & \text{if} \quad i_{j,t} = 0 \\ \omega^k > 0 & \text{if} \quad i_{j,t} \neq 0 \end{cases}$$

The parameter $\omega^k > 0$ will be one of the key parameters of the model which I use along the comparative static exercises to measure the contribution of the investment lumpiness induced by non-convex real rigidities on shaping the properties of the cross-sectional distribution of debt issuance.

Debt Financing

Corporate investment, as well as any distribution, can be financed with internal funds generated by operating profits, new issues of equity or new issues of long-term debt. Firm j-th incurs a cost $\Omega^b(a_{j,t})$ each time it decides to change the amount of debt outstanding from $b_{j,t}$ to $b_{j,t+1}$; where $a_{j,t} \equiv b_{j,t+1} - (1-\lambda)b_{j,t}$ represents the firm's new bond issuance. Note that in the context of long-term debt, each period only a fraction $\lambda \in (0,1)$ of the face-value is paid back to bondholders. Then, similar to the non-convex real cost function, $\Omega^b(a_{j,t})$ corresponds to a fixed cost incurred when new debt is issued, i.e.,

$$\Omega^b(a_{j,t}) = \begin{cases} 0 & \text{if} \quad a_{j,t} = 0 \\ \omega^b > 0 & \text{if} \quad a_{j,t} \neq 0 \end{cases}$$

where ω^b represents the second key parameters of the model used in the comparative static exercises performed in Section 3.5. Note that this type of debt issuance cost function has also been implemented by other works (e.g. Kuehn and Schmid (2014)).

Equity value

The firm j-th's shareholders receive dividends as long as the firm is operating. Distributions to shareholders, $d_{j,t}$ are given by equity payout $e_{j,t}$ net of issuance costs. In the model, equity payouts of a firm j-th are equal to the firm's operating profit net of cash flows from its financing and investment activities,

$$\begin{aligned} e_{j,t} \equiv e(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) \ = \ (1-\tau)\,\Pi_{j,t} \ + \ \tau\delta k_{j,t} \ - \ \Big(i_{j,t} + \Omega^k(i_{j,t})\Big) \ - \ (c(1-\tau)+\lambda)\,b_{j,t} \\ + \ \Big(P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t)\,(b_{j,t+1} - (1-\lambda)b_{j,t}) \ - \ \Omega^b(a_{j,t})\Big) \end{aligned} \tag{3.4}$$

with $\tau \in (0,1)$ as the firm's effective tax rate and Γ_t the vector of aggregate states of the economy $(\Delta x_t, s_t, \mu_t)$.[26] The first term of equity payouts captures the firm's operating profit, from which the required investment expenses, $i_{j,t} + \Omega(i_{j,t})$, and debt repayments, $(\lambda + c(1-\tau))\,b_{j,t}$ are deducted. Note that capital depreciation and debt interest payment generate tax shields. The debt price function $P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t)$ is such that it will be a function of the current vector of stochastic variables $(z_{j,t}, \Gamma_t)$ and optimal decisions at time t. The value of the firm to its shareholders denoted by $J_{j,t}$ considers the present value of distributions $d_{j,t}$ plus the expected firm's continuation value.

$$J_{j,t} \equiv J(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) \ = \ \max\Big\{0, \max_{k_{j,t+1}, b_{j,t+1}} \Big\{d(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) + \mathbb{E}_t(M_{t,t+1} \times J_{j,t+1})\Big\}\Big\} \tag{3.5}$$

where $M_{t,t+1}$ is the equilibrium stochastic discount factor derived from the representative household's preferences.[27] Furthermore, in the model, the equity issuance cost is modeled as a fixed cost $\psi_e > 0$ that is paid if equity payouts turn out to be negative. Then, the firm's distributions are computed as $d_{j,t} \equiv e_{j,t} - \psi_e \times \mathbb{I}_{\{e_{j,t}<0\}}$, where $\mathbb{I}_{\{e_{j,t}<0\}}$ denotes an indicator function that takes value of one when $e_{j,t}$ is negative and zero otherwise. Lastly, note that the first *max* operator in equation (3.5) captures the limited liability of shareholders, whereas the second *max* operator relates to the determination of the optimal decisions of the firm's manager regarding next-period capital and debt outstanding.

Default

Shareholders' limited liability implies that equity value, $J_{j,t}$, is bounded and will never fall below zero. This implies that equity holders will default on their credit obligations whenever their idiosyncratic shock $z_{j,t}$ is below a cutoff level $z^{\star}_{j,t} \equiv z^{\star}(k_{j,t}, b_{j,t}, \Gamma_t)$ determined by the threshold default condition, $J(k_{j,t}, b_{j,t}, z^{\star}_{j,t}, \Gamma_t) = 0$. To simplify the notation below, I define $z^0_{j,t} = z^{\star}(k_{j,t}, 0, \Gamma_t)$ which represents the idiosyncratic shock realization that makes the unlevered firm's value equal to zero; i.e. the lowest

[26] The normalized version of the model, which is described in the Appendix B.2.1, depends on the growth rate of the aggregate technology shock Δx_t instead of the level of the aggregate technology shock x_t. The aggregate state μ_t denotes a measure over the distribution of capital stocks ($k_{j,t}$), debt outstanding ($b_{j,t}$), and idiosyncratic shocks ($z_{j,t}$); which is characterized in the definition of the recursive equilibrium in the Appendix B.2.3.

[27] The stochastic discount factor derived from the household's maximization problem is described in Appendix B.2.3.

value of $z_{j,t}$ at which the unlevered firm keeps operating.

Debt Contracts

At period t, the representative financial intermediary allows a firm j-th to change its debt outstanding to $b_{j,t+1}$ by buying corporate debt at price $P_{j,t} \equiv P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t)$ and collect coupon and principal payments until the firm's manager decides to default. If default occurs at period t, shareholders walk away from the firm, while the financial intermediary recovers a fraction $(1-\chi) \in (0,1)$ of the unlevered firm's value. As in Khan et al. (2014), I assume the remainder of any defaulting firm's value is lump-sum rebated to households so that default implies no direct loss of resources. Under these assumptions, period-t per unit market price of debt $P_{j,t}$, is pinned down by an arbitrage condition such that the amount of money creditors are willing to pay for the contract must equal the expected value of future payments. Formally, this condition implies,

$$\begin{aligned} b_{j,t+1} \times P_{j,t} &= \mathbb{E}_t\Big(M_{t,t+1} b_{j,t+1}(\lambda + c + (1-\lambda)\cdot P_{j,t+1}) \underbrace{\mathbb{I}_{\{z^{\star}_{j,t+1} < z_{j,t+1}\}}}_{\text{solvent states}}\Big) \\ &\quad + \mathbb{E}_t\Big(M_{t,t+1}(1-\chi) J(k_{j,t+1}, 0, z_{j,t+1}, \Gamma_{t+1}) \underbrace{\mathbb{I}_{\{z^{0}_{j,t+1} < z_{j,t+1} < z^{\star}_{j,t+1}\}}}_{\text{default states}}\Big) \end{aligned} \tag{3.6}$$

The first term on the right-hand-side of equation (3.6) contains the cash flows received by bondholders if no default takes place at period $t+1$; whereas the second term reflects the payments upon default net of deadweight costs.

3.3.2 Aggregate state of the economy

As standard in DGSE models with heterogeneous agents (Krusell and Smith (1998)), the aggregate state of the economy will be described by the vector $\Gamma_t \equiv (\Delta x_t, s_t, \mu_t)$, where $(\Delta x_t, s_t)$ represents the vector of aggregate shocks and μ_t denotes a measure over the distribution of capital stocks $(k_{j,t})$, debt outstanding $(b_{j,t})$, and idiosyncratic shocks $(z_{j,t})$. To close the economy, I specify the law of motion of μ_t as the mapping Γ_t that satisfies $\mu_{t+1} = \Gamma(\Delta x_{t+1}, s_{t+1}, \mu_t)$. Γ_t is characterized in the definition of the recursive equilibrium that I describe in the Appendix B.2.3.

Following Krusell and Smith (1998), I do not model the measure μ_t completely. Instead, I proxy it by using only some moments of the aggregate distribution that I include as aggregate variables. Then, for each element of the aggregate state space, I allow firms to form expectation about other aggregate variables (such as consumption, and wages) that allow them to solve their maximization problem each period.[28]

[28] As described in Appendix B.2.4, the belief formation process adds an extra layer of iteration in the numerical solution.

3.3.3 Household problem

I close the model with a unit measure of identical households. Representative household's has Epstein and Zin preferences and holds her wealth invested in (i) one-period noncontingent bonds issued by the perfectly-competitive financial intermediary; and, (ii) firms' shares. The investment in one-period bonds and shares are represented by m_t^b and the measure $\{m_{j,t}^s\}$, respectively.

Then, given prices (dividend-inclusive) the representative household receives for their current shares $\left(p^0(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t)\right)$, the risk-free bond price $(P_f(\Gamma_t))$, and the real wage $(w(\Gamma_t))$; she chooses paths of consumption C_t, hours worked N_t, new bond holdings m_{t+1}^b, and the numbers of news shares $\{m_{j,t+1}^s\}$ to purchase at ex-dividend prices $\left(p^1(k_{j,t+1}, b_{j,t+1}, z_{j,t+1}, \Gamma_t)\right)$ in order to maximize her lifetime utility flows.[29,30] The representative household receives as a lump-sum rebate, $(T(\Gamma_t))$, both the net proceeds of corporate income taxes as well as the remainder of any defaulting firms' value not recovered by the financial intermediary.[31] The lifetime household's utility maximization problem is,

$$H_t \equiv H(\{m_{j,t}^s\}, m_t^b, \Gamma_t) = \underset{\{C_t, N_t, \{m_{j,t+1}^s\}, m_{t+1}^b\}}{Max} \left\{ (1-\beta)\, \widehat{C}(C_t, N_t)^{1-\frac{1}{\psi}} + \beta\, \mathbb{E}_t \left(H_{t+1}^{1-\gamma} \mid \Gamma_t \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\psi}}}$$

$$\text{subject to : } \quad C_t + P_f(\Gamma_t) \times m_{t+1}^b + \int_S p^1(k_{j,t+1}, b_{j,t+1}, z_{j,t+1}, \Gamma_t) m^s(d(k_{j,t+1} \times b_{j,t+1} \times z_{j,t+1}))$$
$$\leq \quad w(\Gamma_t) \times N_t + m_t^b + \int_{S^*} p^0(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) m^s(d(k_{j,t} \times b_{j,t} \times z_{j,t})) + T(\Gamma_t)$$

where γ is the coefficient of relative risk aversion, ψ is the elasticity of intertemporal substitution, and β is the household's subjective discount factor. The contemporaneous component of the utility function is represented by $\widehat{C}(C,N) \equiv C_t^{1-\nu}(1-N_t)^{\nu}$, where $\nu \in (0,1)$ controls the relative preference for labor. The space S represents the product space $\mathbb{R}^+ \times \mathbb{R}^+ \times \mathscr{Z}$; where $\mathscr{Z}$ denotes the space of the idiosyncratic technology shock $z_{i,j}$. Whereas, the space S^* denotes the product space that includes solvent firms. The recursive equilibrium of this economy is characterized in the Appendix B.2.3.

3.4 Model parametrization

In this section, I describe the benchmark calibration of the model. I cite related works that I use as references to guide part of this calibration. I also provide details on the moments targeted to set some of the parameters. As described in Appendix B.2.4, the model is solved using a global method.

[29] Households have access to state-contingent claims. But, since there is no heterogeneity across households, these securities are in zero net-supply at the equilibrium. So, I do not explicitly model them.

[30] Although, $z_{j,t+1}$, is drawn by individual firms at the start of the next period, the household can choose its ownership of type $(k_{j,t+1}, b_{j,t+1}, z_{j,t+1})$ firms as well as its long-term bonds in the current period, since she knows the transition probabilities of $z_{j,t}$ and the law of large numbers applies.

[31] As in Khan et al. (2014), I assume that corporate default implies no direct loss of resources. This assumption, in conjunction with the presence of a perfectly competitive representative financial intermediary, allows to define the model's recursive equilibrium described in the Appendix B.2.3.

3.4.1 Calibration

Preference and standard real business cycles parameters of the model are set to values taken from the existing literature. The remaining set of parameters are chosen in order to match aggregate moments and moments derived from the cross-sectional distribution of debt issuance as well as investment rate in the data. All parameters values of the quarterly calibration implemented are reported in Table 3.2. Preference parameters are standard in the long-run risk literature (Bansal and Yaron (2004)). The elasticity of intertemporal substitution ψ is set to 2 and the coefficient of relative risk aversion γ is set to 10, as in Kung (2015). The subjective discount factor β is set to 0.994 in order to match the average risk-free rate. The relative preference for labor, ν, is set such that the household works $^1/_3$ of her time endowment in the steady state.

On the technology side, I follow Bachmann and Bayer (2014) to set production function. Firms' capital share α is set to 0.20 and the parameter controlling the labor share $\widehat{\alpha}$ is set to 0.50. The depreciation rate of capital δ is set to $9.4\%/4$ to match the average aggregate investment rate in the data. The productivity process is calibrated following Kuehn and Schmid (2014). Within the model, the aggregate Markov chain (s_t) jointly affects the drift and volatility of the growth rate of the aggregate productivity shock x_t and the dispersion of the idiosyncratic technology shock. Specifically s_t consists of five states. To calibrate the Markov chain, I set the persistence of the Markov chain (ρ) to 0.95. Following Kuehn and Schmid (2014), the mean and volatility of the drift states of the aggregate growth rate $(\mu_x(s_t))$ are set to zero and $1.48e^{-3}$, respectively. Whereas, the mean and volatility of the variance of the aggregate growth rate $(\sigma_x(s_t))$ are set to $2.6e^{-4}$ and $1.8e^{-5}$, respectively. This calibration allows to match the annualized output and consumption growth moments and also obtain a sizable aggregate stock returns volatility. I set g to yield an annual average growth of about 1.8%.

Following Bachmann and Bayer (2014), I set the volatility $\bar{\sigma}$ and persistence of the idiosyncratic productivity process ρ_z to $0.091/2$ and 0.90 respectively; which allows me to match the aggregate default rate. Firms face proportional costs of production, f, of 0.05, similar to Gomes et al. (2003b) which I use to match the average book leverage ratio and the aggregate investment-to-output ratio. The effective corporate tax rate τ is set to 14%, consistent with Binsbergen et al. (2010). The annual coupon payment, c, is set to 3.0%. The bankruptcy deadweight cost χ is set as in Bazdresch (2005), whereas the parameter controlling the average debt maturity, λ, is set to match observed average maturity in corporate bonds traded in the NAIC database. Lastly, the equity issuance fixed cost parameter ψ_e is set to match the frequency of equity issuance. The remaining parameters controlling the non-convex costs hampering capital and debt stocks adjustment, (ω^k, ω^b), are set to match average moments of the cross-sectional investment and debt issuance distribution. Specifically, I choose to target average skewness of the cross-section distributions; that is, 3.4 and 1.9 respectively.

3.5 Quantitative results

In this section, I assess quantitatively the contribution of the non-convex costs affecting the adjustment of the stock of debt and capital, (ω^k, ω^b), on determining the time-series dynamics of the cross-sectional dispersions of debt issuance and investment rates. Since most of the parameters of the model are set to match empirical aggregate moments, I start in Section 3.5.1 evaluating the ability of the benchmark model to produce simulated data supporting aggregate moments similar to their empirical counterparts (Table 3.3).

Furthermore, to completely assess the performance of the benchmark calibration, in Section 3.5.2 I report multiple moments of the cross-sectional debt issuance and investment rate distribution obtained from the model's simulated data. Specifically, I conduct several comparative statics in terms of the investment (ω^k) and debt issuance (ω^b) non-convex costs. The main objective is to quantify the contribution of both rigidities on determining the distribution of debt issuance and investment rate in terms of their: (i) coefficient of asymmetry (skewness), (ii) time-series correlation with the aggregate output of the fraction of firms showing positive debt issuance as well as investment spikes, and; (iii) time-series correlation with the business cycle of the cross-sectional dispersion of the distributions.

3.5.1 Aggregate moments

Table 3.3 shows the aggregate moments produced by simulating the model under the benchmark calibration and compares them with their empirical counterparts.

Panel A shows that the benchmark calibration generates an average investment-to-output ratio of 18% in line with the 20% obtained from the data. Furthermore, the output volatility $\sigma_{\Delta y}$ and relative macro volatilities of consumption and investment are close to the data. Particularly, the annual output volatility $\sigma_{\Delta y}$ in the model is about 3.4%. The consumption annual volatility is about 0.64 of the output volatility; whereas the aggregate investment volatility resulted from the simulations is about 5.4 times the output volatility. The benchmark calibration of the model also replicates correlations across some business cycle variables such as the procyclicality of consumption. The implied persistence of output and investment are also quite close to the ones in the data.

In terms of the aggregate capital structure, Panel B shows that the model produces a book leverage which seems to be in line with its empirical counterpart (0.28). The frequency of equity issuance produced by the model (7%) shows that the equity issuance friction (ψ_e) in the model is reasonable. Default rates, which are importantly affected by the calibration of the idiosyncratic technology dispersion in the model, resulted in line with their empirical counterpart. Also, Panel B shows the importance of having in the model both, a countercyclical price of risk in conjunction and countercyclical uncertainty. Indeed, since these two ingredients together render corporate bonds' credit spread countercyclical (Chen (2010), Kuehn and Schmid (2014)), firms' financing decisions becomes importantly influenced by aggregate economy shocks. In particular, within the model, firms tend to substitute equity for debt financing during recessions. Panel B shows that on average debt issuance correlates positively with the business cycle whereas aggregate equity issuance shows a slightly countercyclical pattern.

Table 3.3 Panel C reports some asset pricing moments from the model's simulations. The model generates a large equity risk premium of about 6.8% per year, and produces substantial variations in excess returns. The annualized standard deviation of excess stock returns is about 8.0%. The strong demand for precautionary savings to alleviate aggregate uncertainty shocks drives the risk-free rate down to 1.64%. The volatility of the risk free rate is also low (1.71%). The model generates a sizable credit spreads of 83bps which exhibits substantial time-series variation. The standard deviation in the model is 69bps and about 44bps in the data.

In the following section of the chapter, I focus on assessing the performance of the model in terms of its cross-sectional implications. In particular, I report multiple moments of the cross-sectional debt issuance and investment rate distribution obtained from the model's simulations and compare them to the main findings exhibited in Table 3.1.

3.5.2 Assessing contribution of real and financial non-convexities

In this section, I assess the cross-sectional implications of the model. In particular, I use the model's simulations to quantify the contribution of the real and financing non-convex rigidities on determining the cross-sectional distribution of both debt issuance and investment rates. To conduct this analysis, I report in Table 3.4 and 3.5 the result of multiple comparative statics in terms of the variables of the model represented by ω^k and ω^b.

Effect on average cross-sectional asymmetry: Panels A in Table 3.4 and 3.5 show the model's predictions about the asymmetry (skewness) of the cross-sectional distribution of debt issuance and investment rate respectively, for different values of (i) the non-convex capital adjustment cost (increasing along rows) and; (ii) the non-convex debt issuance cost of (increasing along columns). As showed in Panels A, the model's simulations indicate that a combination of both non-convex costs are required to reproduce the sample skewness of the firm-level distribution of debt issuance and investment rate.

Within the model, a low non-convex cost of capital adjustment $\left(\omega^k\right)$ reduces not only the asymmetry on the cross-sectional investment rate (Table 3.5 Panel A); but also makes the cross-sectional debt issuance distribution less asymmetric (Table 3.4 Panel A). In the context of more flexible investment, firms react more frequently adjusting their capital in good and bad times. Within the model, aggregate uncertainty is countercyclical. And at the equilibrium of the model with low adjustment real costs, positive adjustments of capital stock in good times are as frequent as negative adjustments of capital stock in bad times.[32] This ends up reducing the overall asymmetry of the cross-sectional distribution of investment rates (Table 3.5 Panel A, along the rows). Within the model, aspects of the

[32]In the model, a modest level of the non-convex real friction (the lowest level used in the comparative static exercises is $0.5 \times \omega^k$) supports a slightly positive skewed distribution of investment even in the presence of countercyclical uncertainty.

firms investment decisions are also reflected on firms' financial needs. Furthermore, in the presence of equity financing rigidities ($\psi_e > 0$), patterns of investment decisions will also affect debt issuance decisions. Then, in this context of a low value of the real non-convex cost, adjustments of the debt and capital stock will be on average more symmetric and thus show a low average skewness coefficient (Table 3.4 Panel A, along the rows). In contrast, a high non-convex real cost makes not only large adjustment of the capital stock more likely; but also in this context, negative large adjustments in bad times will become less likely. In response to high uncertainty in bad times most firms facing important non-convex real rigidities will choose to postpone their decisions and wait, holding their capital stock unchanged. On the other hand, in good times, low uncertainty and a positive economic environment will motivate firms to readjust their capital stock. This will ends up increasing the average uncertainty of the investment rate distribution reflected on a high skewness coefficient. In the context of equity financing rigidities, large positive debt issuance will also increase importantly in good times. In general, despite that firms will tend to maintain a stable level of debt stock in order to balance tax-benefits of debt and the risk of bankruptcy cost by adjusting it frequently, firms facing large financial needs in good times due to high capital expenses will increase importantly debt issuance at these periods. Thus, when non-convex real costs are high, the debt issuance distribution will also become on average positive skewed.

Table 3.4 and 3.5 in Panel A show that the non-convex financial cost $\left(\omega^b\right)$ also increases both the asymmetry of the cross-sectional debt issuance and investment rate distributions. A larger non-convex financial cost will hamper the frequent adjustment of the debt stock intended to balance the tax-benefit of debt and costs associated to bankruptcy risk. In fact, in the model, when the non-convex of issuing debt increases firms tend to adjust their debt stock more importantly in periods where investors value corporate bonds the most (periods of low credit spreads); i.e. in good times. Furthermore, in the presence of non-convex real rigidities, periods where credit spread are low will also coincide with periods of large financial needs to fund large positive investment decisions; which will render the debt issuance distribution more positive skewed. The effect of a larger non-convex debt issuance cost on the asymmetry of the investment rate distribution is twofold. First, while a larger debt issuance cost will make more difficult the funding of large positive investment in good times which will lowers its asymmetry; a larger debt issuance cost will also reduce the possibility of financing small positive changes of the capital stock which will contribute to the positive skewness of the distribution. Note that the contribution of a higher debt issuance cost $\left(\omega^b\right)$ to an increase of the average skewness of investment rate distribution is lower, the higher is the real rigidity faced by firms. Intuitively, when the non-convex real cost is high enough, an increase on the debt issuance cost will mainly affect the investment decisions of those firms planning to adjust importantly its capital stock in good times. Overall, a higher non-convex debt issuance cost $\left(\omega^b\right)$ increases the asymmetry of both the cross-sectional debt issuance and investment rate distributions.

Effect on time-series dynamics of spikes: As showed in Panels B, the model's simulations indicate that a combination of both non-convex costs are required to reproduce the strong business cycle dynamic exhibit by the fraction of firms exhibiting both positive debt issuance and investment spikes.

A high non-convex real cost makes large adjustment of the capital and debt stock not only more likely but concentrated in booms. In fact, a high non-convex real friction reduces the firms' incentive to scale down capital in response to a higher dispersion of the idiosyncratic shocks in bad times. That is, the value of the option to disinvest in bad times will not be high enough to offset the real fixed cost associated to this decision. On the other hand, even in context of non-convex real costs, in good times some firms will be willing to increase their capital stock in response to good aggregate productivity shocks and low uncertainty. As pointed out by Bachmann and Bayer (2014), this real option effect induced on firms' investment decisions by non-convex real cost makes positive investment spikes more procyclical. In terms of the firms' debt issuance decisions, in the absence of strong financial needs as well as high credit spreads in bad times, firms will not have enough incentives to move away from their desired level of debt in bad times which in general can be accomplished by small adjustment of their debt stock. In contrast, in good times, some of the firms facing large non-convex real costs will also show high financial needs; which in the presence of equity issuance rigidities will also create high debt issuance needs. This will render debt issuance positive spikes more procyclical.

Simulations from the quantitative model reveal that the presence of a non-convex debt issuance cost is also required to reproduce the business cycle dynamics reported in Panel B. When the debt issuance non-convex cost is low, firms will tend to adjust their debt position too frequently and in small changes in order to balance the tax-benefit of debt and the cost of bankruptcy risk. Then, a low non-convex debt issuance cost will lower the importance of large adjustment since many firms are performing marginal adjustments of their debt stock and thus, the procyclicality of positive debt issuance spikes decreases. Furthermore, low non-convex debt issuance costs will also allow firms to finance capital adjustment costs so that they can adjust their capital stock more often; specially in good times when credit spreads are low. Overall, a low non-convex debt issuance cost will reduce the relative importance of large adjustments of capital in good time and thus will reduce their comovement with the business cycle.

Effect on time-series dynamics of the cross-sectional distribution: As it is showed in Table 3.4 and 3.5 Panels C, the ability of non-convex real and financing costs to increase positive spikes of debt issuance and investment in good times makes the cross-sectional dispersion of debt issuance and investment rates also larger in those periods; inducing procyclicality on the cross-sectional dispersions.

As I mentioned before, on average, low levels of non-convex rigidities make large infrequent adjustment of the capital as well as debt stock less likely to occur. This effect should lower the overall dispersion of the distributions. However, in the presence of countercyclical aggregate uncertainty risk, large adjustment will become more infrequent in good times than in bad times. In fact, the countercyclical feature of the dispersion of the idiosyncratic productivity shock will dominate the effect that large positive adjustments of debt and capital stock have in good times on increasing the cross-sectional dispersion of debt issuance and investment rates distributions. Effectively, when non-convex rigidities are low, some firms facing extreme negative shocks in bad times (i.e. in periods when uncertainty is high) will find optimal to apply large adjustments on their capital stock which will be reflected in part on their debt stock which will also experience a negative adjustment in response to the negative prospect of those firms. Consequently, in this case, the cross-sectional dispersion of both debt issuance and investment rate will tend to reflect the business cycle properties of the dispersion of the idiosyncratic productivity shock; which in the benchmark calibration follows an heteroskedastic process with countercyclical volatility (as in Bloom (2009), Bachmann and Bayer (2014)).

More broadly, as indicated in Tables 3.4 and 3.5, the model's simulations predict that a combination of both investment and debt issuance non-convex rigidities —once calibrated to average cross-sectional asymmetry of the debt issuance and investment rate distributions —are required to reproduce the time-series dynamics of the entire cross-sectional distribution of both debt issuance and investment rates.

3.6 Conclusion

In this chapter, I add to the study of the cross-sectional implications of firms decisions by investigating the properties of the firm-level distribution of debt issuance. Interestingly, previous results reported for the firm-level distribution of investment rate also manifest in the distribution of debt issuance. In particular, the cross-sectional dispersion of the firm-level debt issuance is robustly and significantly procyclical. The empirical analysis conducted suggests that this result is driven by large adjustments of the debt stock at the firm level (*debt issuance lumpiness*).

In order to explore to what extent these findings are not just a reflection of the behavior of the cross-sectional distribution of investment rate, I build a general equilibrium model featuring heterogenous firms that face investment and financing decisions in the context of non-convex real and financial frictions. The literature on investment has succeeded explaining the role that non-convex real frictions (fixed physical cost) played on shaping the investment distribution. The calibrated model indicates that although frictions affecting investment decisions directly contribute to the time-series properties of the cross-sectional debt issuance distribution, they are not sufficient to explain moments computed in the data. Particularly, the model's simulations show that non-convex costs of issuing debt are necessary to explain the procyclicality of the dispersion of the firm-level debt issuance distribution and link this behavior to time-series dynamic of extreme adjustment of the debt stock. In contrast, non-convexities affecting investment decision alone are not enough to reproduce these links.

Table 3.1: Statistics of the cross-sectional distribution of debt issuance and investment rates

Panel A	debt issuance		investment rate	
moments of firm-level distr.:	average	corr(·,BP-Y)	average	corr(·,BP-Y)
mean	0.005	0.54 ***	0.017	0.63 ***
	(0.005)		(0.004)	
standard deviation	0.062	0.43 ***	0.022	0.56 ***
	(0.011)		(0.004)	
fraction of firms with (−) spikes	0.059	−0.42 ***	0.015	−0.13
	(0.021)		(0.018)	
fraction of firms with (+) spikes	0.081	0.61 ***	0.051	0.59 ***
	(0.021)		(0.017)	

test of differences between the average fraction of firms with:

	t-test	W-test		t-test	W-test
(+) debt issuance spike and (−) debt issuance spike	−8.64***	−7.97***	(+) inv. spike and (−) inv. spike	−16.62***	−12.15***

Panel B	corr(·,C-S st.dev.)	corr(·,C-S st.dev.)
fraction of firms with (−) spikes	−0.20*	−0.04
fraction of firms with (+) spikes	0.85***	0.94***

(continues)

Panel C	average	corr(·,C-S st.dev.)		corr(·,C-S st.dev.)	
fraction of firms with:					
(+) debt issuance spikes,	0.015	0.75	***	0.91	***
and (+) investment spikes	(0.007)				
(+) debt issuance spikes,	0.066	0.81	***	0.62	***
and no-(+) investment spikes	(0.015)				
no-(+) debt issuance spikes,	0.036	0.51	***	0.87	***
and (+) investment spikes	(0.011)				
(−) debt issuance spikes,	0.003	0.21	*	0.32	**
and (−) investment spikes	(0.003)				
(−) debt issuance spikes,	0.055	−0.22	*	−0.21	*
and no-(−) investment spikes	(0.017)				
no-(−) debt issuance spikes,	0.012	0.03		0.03	
and (−) investment spikes	(0.015)				

Statistics of the cross-sectional distribution of debt issuance and investment ratio. This table shows some empirical facts of the cross-sectional distribution of debt issuance and investment rates. The table is built using the CRSP/Compustat Merged Fundamentals Quarterly from 1984Q1 to 2016Q4. Financing firms (SIC 6000-6999), regulated utilities (SIC 4800-4999), and non-profit firms (SIC 9000-9999) are excluded. Data treatment is explained in Appendix B.1. Data treatment leaves a sample of 363,512 firm-quarterly observations from 11,236 different firms which represents roughly 43 percent of the original database. Balance-sheet data is adjusted by the price level from NIPA. Y denotes the cyclical component of real GDP growth obtained by detrending the time-series using a band-pass (BP) filter. Debt issuance is defined as the change of total debt where total debt is defined as the sum of long- and short-term debt; scaled by total assets. Investment rates are defined as capital expenditures; scaled by total assets. Total assets are computed as the average of last three years assets. Correlation statistics, $\rho(\cdot,\cdot)$ are constructed by applying a band-pass filter to the deflated variable. Positive (negative) investment spikes are defined as investment rate higher (lower) than 5% (-5%) of total assets; as in Doms and Dunne (1998), Gourio and Kashyap (2007) and Bachmann and Bayer (2014) for quarterly data. Positive (negative) debt issuance spikes are defined as debt issuance higher (lower) than 5% (-5%) of total assets. Panel A shows on the second (fourth) column the sample average of the mean, standard deviation, fraction of firms with negative debt issuance (investment) spikes, and fraction of firms with positive debt issuance (investment) spikes. Standard errors are reported in parenthesis. Panel A shows in the third (fifth) column the correlation with the band-passed GDP growth exhibited by the mean, standard deviation, fraction of firms with negative debt issuance (investment) spikes, and fraction of firms with positive debt issuance (investment) spikes. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Panel A also shows the results of two tests of differences applied to the average fraction of firms exhibiting positive spikes and the average fraction of firms exhibiting negative spikes. "W-test" denotes the statistic obtained from Wilcoxon test. These test are applied to both the debt issuance and investment rate cross-sectional distribution. Panel B shows in the second (third) column the correlation between the fraction of firms exhibiting debt issuance (investment) spikes and the cross-sectional dispersion of the firm-level debt issuance (investment rate) distribution. Panel C shows in the third (fourth) the correlation between the sample average of the fraction of firms exhibiting debt issuance and/or investment spikes and the cross-sectional dispersion of the firm-level debt issuance (investment rate) distribution.

Table 3.2: Benchmark quarterly calibration

Parameter	Description	Value
A. Preferences		
β	discount factor	0.994
γ	relative risk aversion	10.0
ψ	elasticity of intertemporal substitution	2.0
B. Production		
α	capital share parameter	0.20
$\widehat{\alpha}$	labor share parameter	0.50
δ	capital depreciation rate	0.094/4
f	operational (proportional) cost	0.05
ω^k	non-convex real capital adjustment cost	0.22
C. Productivity		
g	growth rate of consumption	0.018/4
ρ	persistence of aggregate state s_t	0.95
$\bar{\sigma}$	conditional volatility of the idiosyncratic shock	0.091/2
ρ_z	persistence of idiosyncratic shock	0.90
D. Finance		
τ	tax rate	0.14
λ	parameter controlling average debt maturity	0.10
c	coupon rate	3.0%/4
ω^b	non-convex debt issuance cost	0.04
ψ_e	equity issuance cost: fixed component	0.06
χ	bankruptcy deadweight cost	0.70

Benchmark quarterly calibration. This table reports the parameter values used in the benchmark quarterly calibration of the model. Section 3.4 describes the moments targeted to set each parameter.

Table 3.3: Aggregate business cycle, and financing moments

Moment	Data	Model
A. Business cycle		
$E(\Delta y)(\%)$	1.80	1.97
$E(I/Y)$	0.20	0.18
$\sigma_{\Delta y}(\%)$	3.56	3.37
$\sigma_{\Delta c}/\sigma_{\Delta y}$	0.71	0.64
$\sigma_{\Delta i}/\sigma_{\Delta y}$	4.50	5.38
$ACF_1(\Delta y)$	0.35	0.29
$ACF_1(\Delta i)$	0.85	0.71
$corr(\Delta c, \Delta y)$	0.39	0.43
B. Financing		
Book leverage	0.26	0.28
Freq. of equity issuance	0.09	0.07
Default rate (%)	0.84	1.79
$corr(\text{debt issuance}, \Delta y)$	0.54	0.62
$corr(\text{equity issuance}, \Delta y)$	-0.45	-0.19
C. Asset prices		
$E(r_e - r_f)(\%)$	7.22	6.79
$\sigma(r_e - r_f)(\%)$	16.5	8.07
$E(r_f)(\%)$	1.51	1.64
$\sigma(r_f)(\%)$	2.2	1.71
$E(cs)(\text{bps})$	90	83
$\sigma(cs)(\text{bps})$	44	69

Aggregate business cycle and financing moments. I/Y denotes the investment-output ratio. Δy, Δc, Δi denote output, consumption, and investment growth respectively. $r_e - r_f$ is the aggregate stock market excess return, r_f is the one-period real risk-free rate, and cs is the aggregate credit spreads. The model;s moments are calculated by simulating the model for 5,000 firms and 10,000 quarters, with a 1,000-quarters burning period. Aggregate returns and credit spreads are equally-weighted. Growth rates, and returns moments are annualized percentage. credit spreads are in annualized basis point units. Average default rates for the data corresponds to average expected default rates resulted from implementing the KMV model in the panel data described in previous chapter. Refer to Table 2.2 in previous chapter for the definition of most variables of the data.

Table 3.4: Effect of non-convex costs on the moments of the cross-sectional distribution of debt issuance

Panel A

Skewness of debt issuance distribution					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	0.29	1.21	2.09	2.72	3.31
$0.75\times\omega^k$	0.56	1.81	2.81	3.86	4.46
$1.00\times\omega^k$	0.83	2.17	3.53	4.53	5.04
$1.25\times\omega^k$	0.95	2.53	3.78	4.57	5.34
$1.50\times\omega^k$	1.07	2.57	3.95	4.86	5.62

Panel B

Corr(Fraction of $(+)$ debt spike adjusters, BP-Y)					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	0.21	0.35	0.49	0.63	0.76
$0.75\times\omega^k$	0.25	0.42	0.57	0.71	0.8
$1.00\times\omega^k$	0.28	0.48	0.65	0.76	0.83
$1.25\times\omega^k$	0.33	0.52	0.71	0.79	0.84
$1.50\times\omega^k$	0.36	0.56	0.72	0.8	0.8

Panel C

Corr(Standard deviation of debt issuance, BP-Y)					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	-0.18	0.08	0.33	0.55	0.71
$0.75\times\omega^k$	-0.08	0.08	0.23	0.39	0.53
$1.00\times\omega^k$	-0.05	0.21	0.45	0.62	0.77
$1.25\times\omega^k$	-0.05	0.11	0.25	0.41	0.54
$1.50\times\omega^k$	0.04	0.29	0.49	0.65	0.76

Effect of non-convex costs on the moments of the cross-sectional distribution of debt issuance. This table shows the effect that both debt and capital adjustment non-convex costs (ω^k, ω^b) exhibit in the model on the cross-sectional and time-series properties of the firm-level debt issuance distribution. Model variables and statistics are calculated by simulating the model for 5,000 firms and 10,000 quarters, with a 1,000-quarters burning period. Panel A shows the effect of both non-convex rigidities on the skewness of the debt issuance distribution. Panel B shows the impact of both non-convex costs on the correlation with the business cycle of the fraction of firms exhibiting large infrequent positive adjustment in the debt stock. Panel C shows the impact of both non-convex costs on the correlation with the business cycle of the dispersion of the firm-level debt issuance ratio distribution. Refer to Table 3.1 for details about variables' definitions.

Table 3.5: Effect of non-convex costs on the moments of the cross-sectional distribution of investment rate

Panel A

Skewness Investment rate					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	0.13	0.43	0.71	0.85	0.97
$0.75\times\omega^k$	1.18	1.43	1.51	1.81	1.92
$1.00\times\omega^k$	2.17	2.25	2.27	2.43	2.49
$1.25\times\omega^k$	2.61	2.67	2.74	2.85	2.89
$1.50\times\omega^k$	2.96	3.08	3.09	3.21	3.20

Panel B

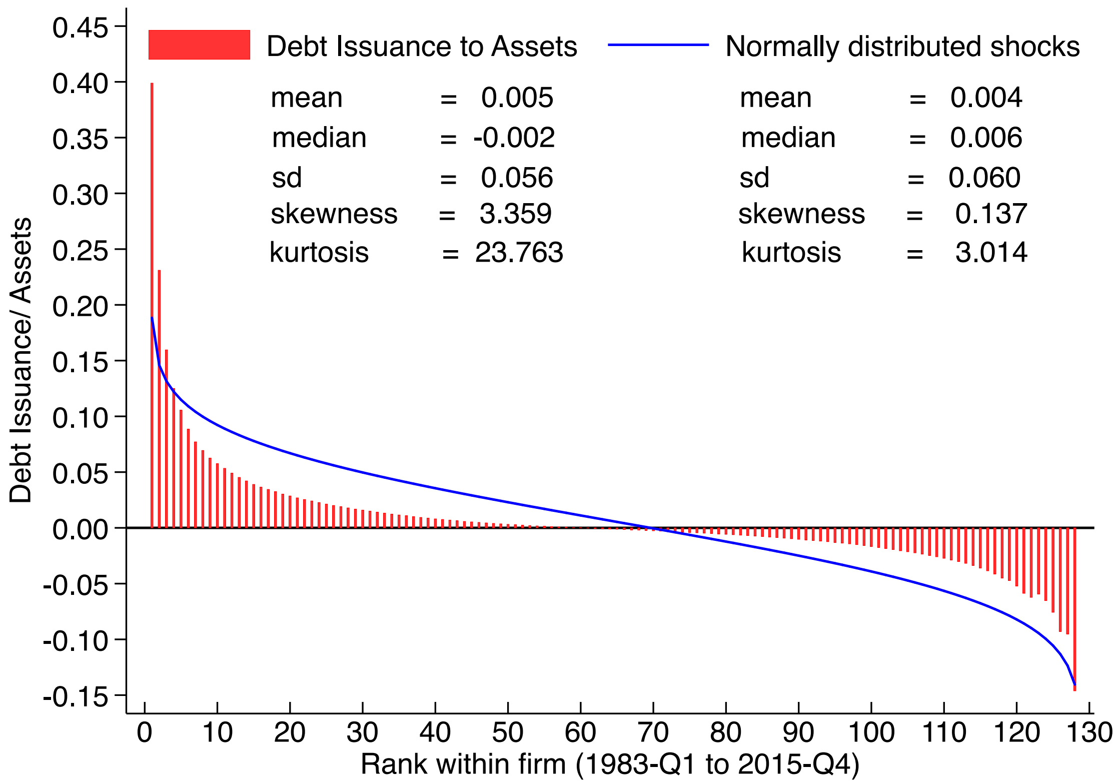
Corr(Fraction of investment spike adjusters, BP-Y)					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	0.05	0.1	0.13	0.14	0.14
$0.75\times\omega^k$	0.24	0.29	0.34	0.35	0.34
$1.00\times\omega^k$	0.42	0.47	0.51	0.52	0.53
$1.25\times\omega^k$	0.52	0.52	0.61	0.64	0.65
$1.50\times\omega^k$	0.49	0.56	0.63	0.66	0.68

Panel C

Corr(Standard deviation of investment rate, BP-Y)					
	$0.50\times\omega^b$	$0.75\times\omega^b$	$1.00\times\omega^b$	$1.25\times\omega^b$	$1.50\times\omega^b$
$0.50\times\omega^k$	-0.31	-0.19	-0.05	0.02	0.08
$0.75\times\omega^k$	-0.15	0.04	0.23	0.31	0.39
$1.00\times\omega^k$	0.03	0.26	0.49	0.58	0.67
$1.25\times\omega^k$	0.25	0.44	0.59	0.65	0.69
$1.50\times\omega^k$	0.45	0.58	0.66	0.67	0.68

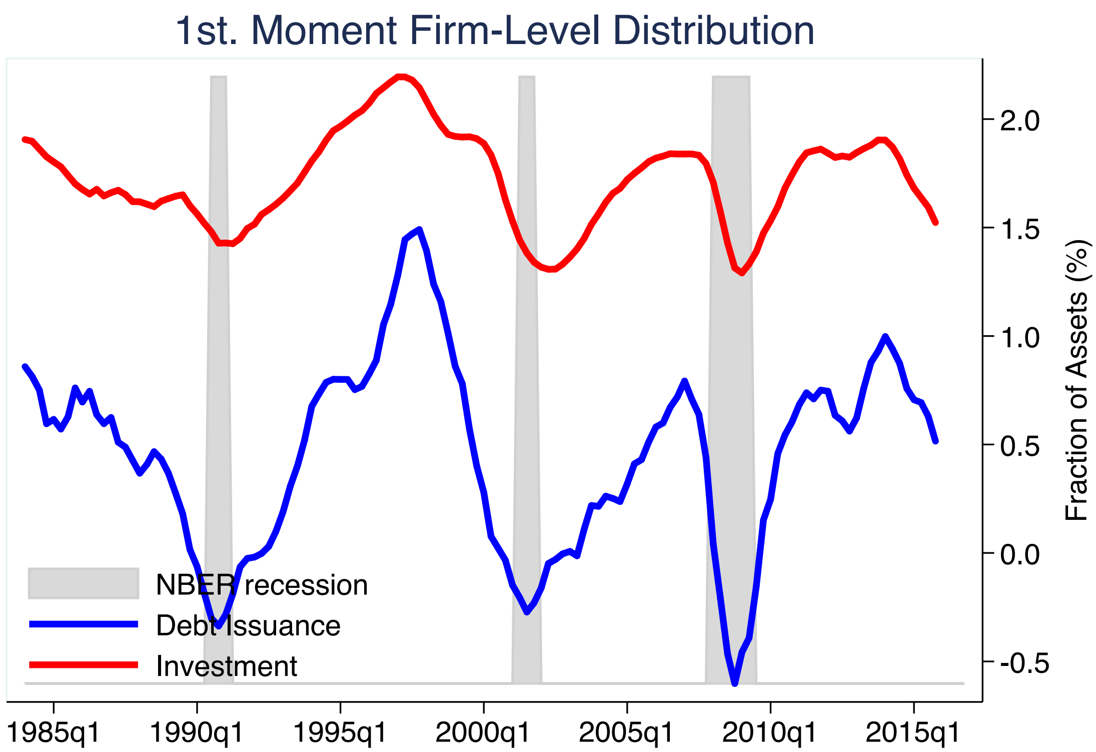
Effect of non-convex costs on the moments of the cross-sectional distribution of investment rate. This table shows the effect that both debt and capital adjustment non-convex costs (ω^k, ω^b) exhibit in the model on the cross-sectional and time-series properties of the firm-level investment rate distribution. Model variables and statistics are calculated by simulating the model for 5,000 firms and 10,000 quarters, with a 1,000-quarters burning period. Panel A shows the effect of both non-convex rigidities on the skewness of the investment rate distribution. Panel B shows the impact of both non-convex costs on the correlation with the business cycle of the fraction of firms exhibiting large infrequent positive adjustment in the capital stock. Panel C shows the impact of both non-convex costs on the correlation with the business cycle of the dispersion of the firm-level investment rate distribution. Refer to Table 3.1 for details about variables' definitions.

Figure 3.1: Average debt issuance cross-sectional distribution



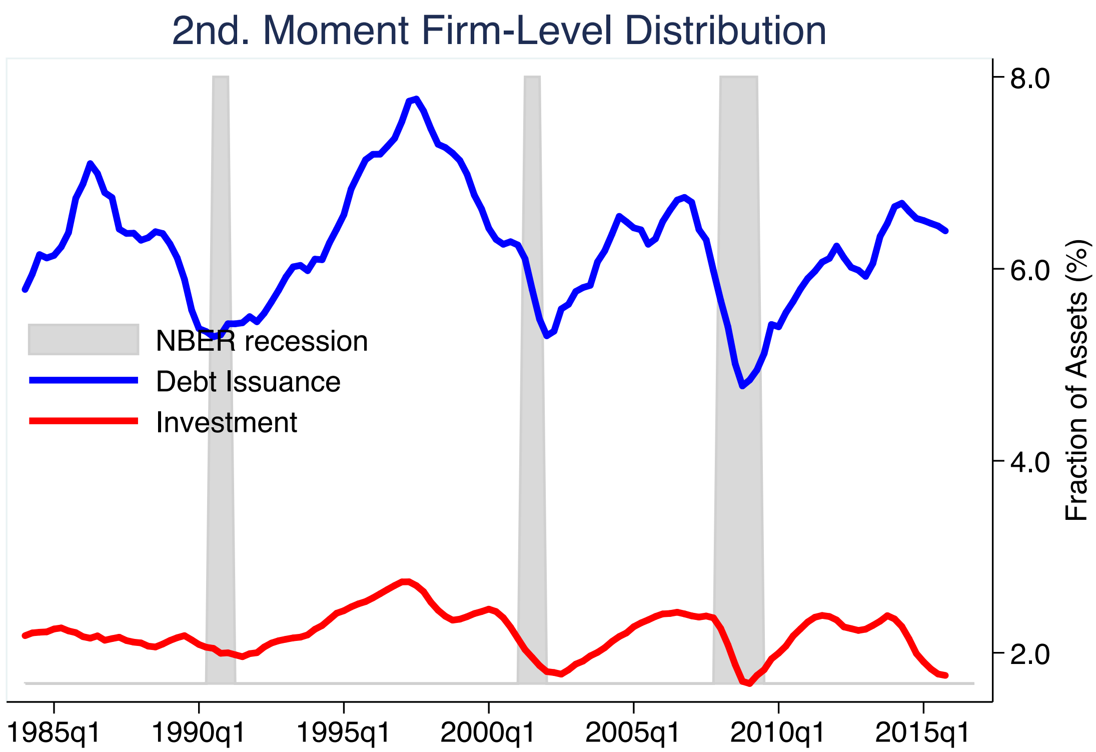
Average debt issuance cross-sectional distribution. This figure is used to compare the average of the observed firm-level debt issuance distribution (red bars) to a normally simulated counterpart (blue line). The figure is constructed using the following steps. First, for each firm, quarterly debt issuance are ranked from the highest to the lowest debt issuance into bins. Next, the simulated debt-issuance counterparts ($x_{j,t}$) of the firm j for each bin i by solving the equation $\Phi_j(x_{j,i}) = {}^{i}/_{N_b}$; where Φ_j represents the cumulative density function of a normal distribution with mean and standard deviation equal to the sample mean and standard deviation of firm j-th quarterly debt issuance. N_b denotes the total number of bins i.e. $4 \times (2016 - 1984 + 1)$. After repeating the exercise for each firm, I construct the averages over all firms by bin. Refer to Table 3.1 for details of the variables' definition.

Figure 3.2: First moment of firm-level debt issuance and investment rate distribution



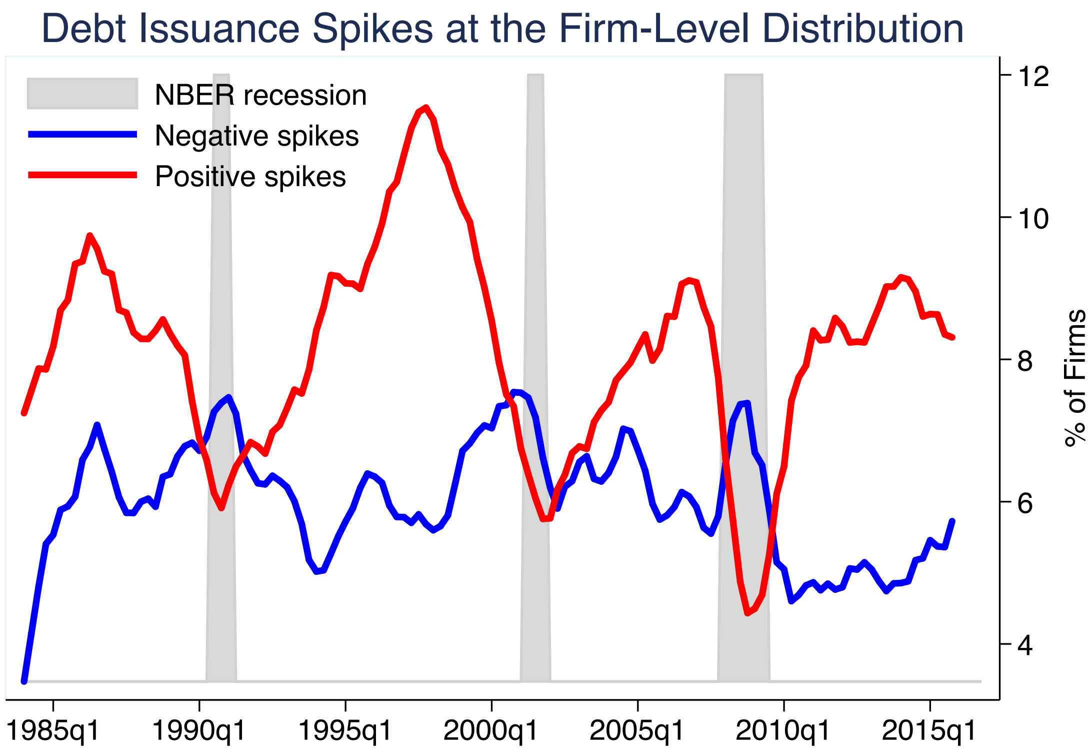
First moment of firm-level debt issuance and investment rate distribution. This figure shows the average of the first moment of the debt issuance (blue line) and investment rate (red line) cross-sectional distribution from 1984Q1 to 2016Q4. The time-series are constructed from the CRSP/-Compustat Merged Fundamentals Quarterly. Debt issuance is defined as the change of total debt scaled by total assets. Total debt is computed as the sum of long- and short-term debt. Total assets are computed as a weighted-average of last-year quarterly assets. The investment rate, is defined as capital expenditures to total assets. For means and pictures, I use the seasonally smoothed variables. Refer to Table 3.1 for details of the variables' definition.

Figure 3.3: Dispersion of firm-level debt issuance and investment rate distribution



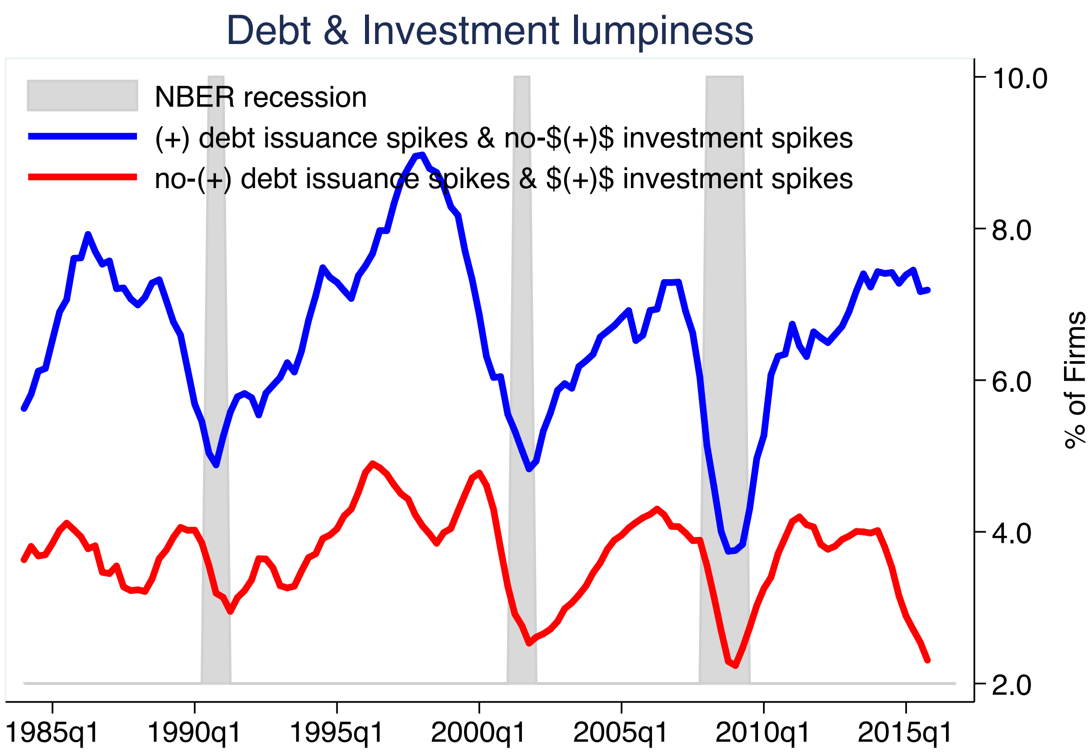
Dispersion of firm-level debt issuance and investment rate distribution. Refer to Table 3.1 for details of the variables' definition.

Figure 3.4: Fraction of firms exhibiting positive and negative debt issuance spikes



Fraction of firms exhibiting positive and negative debt issuance spikes. Refer to Table 3.1 for details of the variables' definition. Positive (negative) investment spikes are defined as investment rate higher (lower) than 5% (-5%) of total assets; as in Doms and Dunne (1998), Gourio and Kashyap (2007) and Bachmann and Bayer (2014) for quarterly data. Positive (negative) debt issuance spikes are defined as debt issuance higher (lower) than 5% (-5%) of total assets.

Figure 3.5: Fraction of firms exhibiting positive investment and debt issuance spikes



Fraction of firms exhibiting positive investment and debt issuance spikes. Refer to Table 3.1 for details of the variables' definition. Positive (negative) investment spikes are defined as investment rate higher (lower) than 5% (-5%) of total assets; as in Doms and Dunne (1998), Gourio and Kashyap (2007) and Bachmann and Bayer (2014) for quarterly data. Positive (negative) debt issuance spikes are defined as debt issuance higher (lower) than 5% (-5%) of total assets.

Chapter 4

Conclusion

This thesis is comprised of two essays on Structural Corporate Finance. In chapter 2, the first essay examines how asset redeployability —through its positive effect on disinvestment flexibilities and negative effect on bankruptcy deadweight cost —affects the cross-section of financial leverage and credit spreads. In the data, firms exhibiting more asset redeployability also show higher leverage ratios and lower credit spreads. Moreover, in the data, the asset redeployability measure contains information that goes over and above information provided by expected recovery rates and a tangibility-based measure. I investigate the economic mechanisms behind these findings by using a structural model that includes varying degrees of disinvestment flexibilities and bankruptcy costs. Importantly, these two ingredients of the model are set to match the differences in expected returns and recovery rate showed by extreme portfolios of firms formed based on a novel measure of asset redeployability. From the model's simulations, I find that portfolios of firms formed based on the degree of the disinvestment flexibility and the bankruptcy costs show significant variation in terms of leverage ratios and credit spreads along the disinvestment-flexibility dimension. Effectively, in the model, firms facing high disinvestment flexibility are able to not only default less but more importantly they default less often in bad times; which, in the presence of a countercyclical price, allows these firms to more and cheaper debt on average. Furthermore, within the model, differences in expected recovery rates between firms are mainly explained by differences in bankruptcy costs. Then, I use this evidence to conclude that the link between asset redeployability and disinvestment flexibility can be a plausible explanation of why in the data, even after accounting for expected recovery rates (and a wide range of controls), asset redeployability still predicts higher financial leverage and lower credit spreads. More generally, this essay provides new evidence to explain the positive effect of asset redeployability on the credit terms of debt. In particular, I add to the literature studying asset redeployability by highlighting its positive effect on firms' value through allowing them to maneuver business cycle fluctuations more effectively. In contrast, traditional economic literature studies the asset redeployability's positive features through mainly focusing on its relation with creditors' recovery values at corporate default.

In chapter 3, the second essay explores time-series dynamics of the entire cross-sectional distribution of debt issuance. Specifically, I add to current macroeconomic works studying debt issuances at the aggregate level by showing that —as the cross-sectional average —, the cross-sectional dispersion of the debt issuance distribution also comoves with the business cycle. Further, I present evidence that suggests that the procyclical pattern of the cross-sectional dispersion of the debt issuance distribution is mainly driven by periods where firms exhibit large and positive investment and debt issuances; that is, periods of aggregate macroeconomic growth. To the extent that investment and debt issuance lumpiness result from the interaction of non-convex real and financial costs, in this essay I focus on understanding the contribution of both frictions on shaping the patterns of the cross-sectional dispersion of debt issuance. To accomplish this goal, I build a DSGE model with lumpy investment and debt financing. I use the model's simulations to conclude that neither a non-convex real cost nor a non-convex financial cost alone can reproduce the pattern exhibited by the cross-sectional dispersion of debt issuance. In a model with countercyclical uncertainty shocks, both non-convex frictions are required to induce a region of inaction in bad times, while allowing high-growth firms to scale up their capital stock in good times through a real option effect. Interestingly, I conclude that the procyclical behavior exhibited by the cross-sectional dispersion of debt issuance is not just a reflection of the properties of the cross-sectional dispersion of investment rates.

4.1 Future work

Both essays presented in this thesis could be extended along several dimensions. For instance, in the model of the first essay, asset redeployability is modeled as an exogenous characteristic of firms' assets. While this assumption simplifies the analysis as well as the numerical solution, I believe it would be interesting to allow firms to choose their degree of asset redeployability by either introducing a second type of capital or; by differentiating new from used capital. This analysis would provide a better understanding about the nature of firms' asset redeployability and therefore, about its implications. Furthermore, the model predicts that differences in disinvestment flexibilities do not produce important differences in expected recovery rates. This prediction could be tested as long as disinvestment flexibility can be properly measured.

Lastly, in the second essay, long-term bonds are assumed to have a constant average maturity. While this assumption allows the model to stay tractable, it would be interesting to explore the implications of the model when debt maturity decisions are also allowed. Indeed, in reality, firms issue debt at multiple maturities. This will certainly have implications for the entire cross-sectional debt issuance distribution; in particular, for the higher-order moments of the distribution. In this context, it would be interesting to study how active debt-maturity managing could affect the features of the cross-sectional distribution of debt issuance as well as investment rates.

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Appendix A

Appendix to Chapter 2

A.1 Data appendix

In this appendix, I describe the construction of firm-level credit spreads and other variables used in the empirical analysis. Section A.1 describes the bond transaction data set used to construct firm-specific credit spreads. Section A.2 provides the details about the construction of the variables used in the estimation of panel regressions and descriptive statistics of these variables. Section A.3 describes the KMV model implemented in the data to construct the expected recovery rates and ultimately used to decompose the asset redeployability measure.

A.1.1 Bond-level data

This chapter uses a sample of U.S. non-financial and non-public-utility firms covered by the S&P Compustat and the Center for Research in Security Prices (CRSP). I obtained secondary market transaction prices of corporate bonds from the National Association of Insurance Commissioners (NAIC). The NAIC Financial Data Repository Database for Corporate Bonds collects all holdings and transactions for insurance companies based on their mandatory quarterly Schedule D filings. The transaction data includes price, date, and quantity. The data covers a specific group of investors, i.e. insurance companies. According to Veronesi (2016), insurances companies make up a very large fraction of the market participants based on their holdings. To be part of the final sample, bonds must be issued by a U.S. firm and pay a fixed coupon. I also eliminate bonds with special bond features such as put, call, exchangeable, asset backed, and convertible (Campbell and Taksler (2003)).

Using security-level daily transaction data, I reconstruct for each individual bond in my sample the promised cash-flows of the corresponding corporate debt instrument. The idea is to construct the promised sequence of cashflows $\{C(s) : s = 1, 2, ..., S\}$ at time t.A bond's cashflows will consist of the regular coupon payments and the repayment of the principle at maturity. Importantly, the timing of the stream of cash flows is determined using information about accrued interests reported in the

NAIC database. Particularly, the next coupon date is set to replicate the reported accrued interests. Then, given the stream of cashflows determined, the (dirty) price in period t of bond k issued by firm i will satisfy the following relation,

$$P_{i,t,k} = \sum_{s=1}^{S} C(s) e^{-r_s s} \tag{A.1}$$

where r_s is the spot rate used to discount a cashflow paid at period $t+s$. Transactions' yields are computed by equating the dirty price to the present value of cash-flows, as in equation (A.1). Then, the bond credit spreads is $S_{i,t,k} = y_{i,t,k} - y_{f,t,k}$, where $y_{i,t,k}$ denotes the benchmark treasury at the date t. To obtain the benchmark treasury for each transaction, I match the bond duration to the zero-coupon Treasury yields curve provided by Gürkaynak et al. (2007) - linearly interpolating if necessary.

To ensure results are not driven by a small number of extreme observations, all observations with credit spreads below 5 basis points and greater than 3,500 basis points are eliminated. Very small corporate issues (par value of less than \$0.1 million) as well as observations with a remaining term-to-maturity of less than one year are also discarded. I also eliminate transactions that involve the the bond issuer and those that show return reversals. These corporate securities were then matched with their issuer's annual balance sheet data from Compustat and daily data on equity valuations from CRSP. This procedure yielded a sample of 16,587 individual transactions over the 1995:M1-2012:M12 period.

A.1.2 Variables description

While our micro-level data on credit spreads reflect month-end values[1], the requisite firm-level balance sheet items from are available annually whereas stock returns are obtained from CRSP file. Issuers' accounting information are matched using the 6-digits issuer Cusip as well as stock prices information. To ensure that all information is included in asset prices, stock returns and bond credit spreads from July of year t to June of year $t+1$ are matched with accounting information for fiscal year ending in year $t-1$. From the annual Compustat data, I construct the following explanatory variables,

- `Market Leverage` : total liabilities / book assets (`at`)
- `Total Liabilities` : long-term debt (`dltt`) + short-term debt (`dlc`) − cash (`che`)
- `Tangibility` : property, plant and equipment / book assets = (`ppent`)/`at`
- `Book-to-Market` : book value equity/market value equity
- `Book Equity` : common/ordinary equity (`ceq`)
  + deferred tax and inv. tax credit (`txditc`)
  − purchase of common and preferred stock (`pstk`)
- `Market Equity` : shares outstanding (`shrout`) × market value stock price (`prc`)

[1]Monthly credit spreads observations are constructing using the last transaction of the month taking into account the time-value of money.

– `ROA` : (operating income after depreciation `oibdp`)/`at`

– `Tobin's Q` : (market equity + `at - ceq` − deferred taxes (`txdb`))/`at`

– `Z-Score` : $3.3 \times \text{ROA} + 1.0\times\left(\frac{\texttt{sale}}{\texttt{at}}\right) + 1.4\times\left(\frac{\texttt{re}}{\texttt{at}}\right) + 1.2\times\left(\frac{\texttt{act-lct}}{\texttt{at}}\right)$

where `re`, `act`, and `lct` denotes retained earnings, current assets, and liabilities, respectively. All the remaining variables' definitions are given in Section 3.2.1.

A.1.3 Variables descriptive statistics

Table A.1 reports the average yield and credit spreads from the NAIC benchmark bond transactions sample described in the previous section, sorted on credit rating. In the sample, 67% of bond transactions lies in the A-BBB categories. Campbell and Taksler (2003) documents a similar pattern. The average monthly spreads between Baa and Aaa bonds is about 144bps, which is consistent to close the average spreads reported by Moody's over the same period. To validate the database used, Figure 2.4, I plot the time series of the average Baa yield spreads obtained from my NAIC sample along with the spreads reported by Moody's over the same period. Note that the two time-series show a similar pattern spiking during the 2000's and the financial crisis. The time series correlation between the two aggregate series is about 0.9.

Table A.2 shows that the term structure of interest rate implicit in the bond sample is, in general, upward-sloping. The term structure of credit spreads shows an increasing pattern for bonds with duration larger than one year.

Table A.3 Panel A reports summary statistics for the bond transaction sample used in the regressions. The size of issue is positively skewed, with an average (median) debt issue of 328 (250) millions. The time-to-maturity of the bonds is long, about 11 years. In general, bond characteristics of my sample are similar to those of previous studies using public debt (see Gilchrist and Zakrajšek (2011)).

Table A.3 Panel B shows individual firm summary statistics. The average firm size in the sample is consistent with previous empirical works' finding regarding the size of firms issuing public debt (Denis and Mihov (2003)). Lastly, Table A.4 reports the average asset redeployability by SIC code which shows similar patterns to that in Table 1 of Kim and Kung (2016).

A.1.4 KMV model

To decompose the asset redeployability measure in two components, I regress this measure on expected recovery rates. Then, the first component was the one explained by expected recovery rates; whereas the residual of this regression corresponded to the second component. Importantly, expected recovery rates were computed based on the KMV model as explained by Bohn and Crosbie (2003), and Altman et al. (2004). In this model, the asset value of the firm V_A is assumed to follow a geometric Brownian motion $dV_A/V_A = \mu\, dt + \sigma_A\, dz$, where μ and σ_A are the firm's asset value drift and volatility rate and dz is a Wiener process. If the total debt at period t is denoted by X_t, default happens if at time

t the value of the firm's assets $V_{A,t}$, is lower than X_t. When default occurs, the recovery rate is given by the ratio of the asset value to the debt, i.e. $V_{A,t}/X_t$. The expected recovery rate is computed as,

$$\mathbb{E}\left(\frac{V_{A,t}}{X_t}\mathbb{I}_{\{V_{A,t}<X_t\}}\right) = \left(\frac{V_{A,0}e^{rt}}{X_t}\right)\left(\frac{\Phi(-d_1)}{\Phi(-d_2)}\right) \tag{A.2}$$

where r is the risk-free interest rate, $\Phi(\cdot)$ is the standard normal cumulative distribution function, and d_1 and d_2 have similar interpretation as in the standard Black-Scholes formula.

The model is implemented by estimating the unobservable parameters of the model regarding the firm's assets at time 0, i.e. V_A and σ_A, through link them to the observable value and volatility of the firm's equity at time 0 denoted as V_E and σ_E, respectively. Specifically, based on the idea that (i) the firm's equity can be seen as a call option on the underlying asset, (ii) debt is homogenous with time of maturity, and (iii) debt coupon rate is zero are zero and dividends are reinvested, standard results show that the value of the equity is,

$$V_E = V_A\Phi(d_1) - e^{-r}X_t\Phi(d_2) \tag{A.3}$$

Furthermore, it is possible to show that the firm's asset and equity volatility are related by the identity,

$$\sigma_E = \sigma_A\frac{V_A}{V_E}\Phi(d_1) \tag{A.4}$$

Given V_E and σ_E - which are approximated by `Market Equity` and the annualized standard deviation of the last twelve monthly excess returns - this system comprised of equation (A.3) and (A.4) has a unique solution. The system is completed by using total liabilities (`dltt + dlc - che`) and the annualized one-month T-Bill as X_t and r, respectively.

A.2 Numerical procedure appendix

This appendix provides details regarding the key elements of the quantitative model and its solution method. Section B.1 describes the stationary version of the model. Section B.2 describes details of the numerical solution method implemented. Section B.3 describes the Euler equations that characterized the optimal firm's decisions. Lastly, Section B.4 provides details of the relation between debt prices and probabilities of default as well as recovery rates used in the model's quantitative analysis.

A.2.1 Shareholders' stationary problem

Assuming that the firm does not default in the current period, and defining the following stationary variables: $\widehat{k}_{t+1} = k_{t+1}/x_t$, $\widehat{i}_t = i_t/x_t$, and $\widehat{b}_{t+1} = b_{t+1}/x_t$; the stationary value function $J(k_t, b_t, \lambda_t, \Gamma_t)/x_t \equiv j(\widehat{k}_t, \widehat{b}_t, \lambda_t, \Gamma_t)$ can be written as,

$$j(\widehat{k}_t,\widehat{b}_t,\lambda_t,\Gamma_t)=\max_{k_{t+1},b_{t+1},\lambda_{t+1}}\left\{\widehat{d}_t+\mathbb{E}_t(M_{t,t+1}e^{\Delta\ln(x_{t+1})}j(\widehat{k}_{t+1},\widehat{b}_{t+1},\lambda_{t+1},\Gamma_{t+1}))\right\} \tag{A.5}$$

where $\Delta\ln(x_{t+1})=\ln(x_{t+1}/x_t)$ and the stationary functions relevant to solve the program are,

$$\begin{aligned}
\widehat{d}_t &\equiv \widehat{e}_t-\Psi(\widehat{e}_t)\\
\widehat{e}_t &\equiv (1-\tau)\widehat{y}_t-\widehat{i}_t-\widehat{\Phi}(\widehat{i}_t,\widehat{k}_t,\omega_t)-(\lambda_t+c(1-\tau))\widehat{b}_te^{-\Delta\ln(x_t)}+\tau\delta\widehat{k}_te^{-\Delta\ln(x_t)}\\
&\qquad +\widehat{P}(\widehat{k}_{t+1},\widehat{b}_{t+1},\lambda_{t+1},\Gamma_t)\left(\widehat{b}_{t+1}-(1-\lambda_t)\widehat{b}_te^{-\Delta\ln(x_t)}\right)\\
\widehat{y}_t &\equiv e^{-\alpha\Delta\ln(x_t)}\widehat{k}_t^{\alpha}-fz_t-\phi\widehat{k}_te^{-\Delta\ln(x_t)}\\
\widehat{i}_t &\equiv \widehat{k}_{t+1}-(1-\delta)k_te^{-\Delta\ln(x_t)}\\
\widehat{\Phi}(\widehat{i}_t,\widehat{k}_t,\omega_t) &\equiv \left(e^{\Delta\ln(x_t)}i_t/k_t-\delta\right)^2\widehat{k}_te^{-\Delta\ln(x_t)}\theta\times\begin{cases}1 & \text{if } i_t>0\\ \omega_t & \text{if } i_t\leq 0\end{cases}
\end{aligned}$$

Note that the debt pricing function can also be normalized,

$$\begin{aligned}
&\widehat{b}_{t+1}\times\widehat{P}(\widehat{k}_{t+1},\widehat{b}_{t+1},\lambda_{t+1},\Gamma_t)=\\
&\quad\mathbb{E}_t\left(M_{t,t+1}\widehat{b}_{t+1}(\lambda_{t+1}+c+(1-\lambda_{t+1})\cdot\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1}))\mathbb{I}_{\{z_{t+1}<z^{\star}_{t+1}\}}\right)\\
&\qquad+\mathbb{E}_t\left(M_{t,t+1}(1-\chi_{t+1})e^{\Delta\ln(x_{t+1})}j(\widehat{k}_{t+1},0,0,\Gamma_{t+1})\mathbb{I}_{\{z^{\star}_{t+1}<z_{t+1}<z^{0}_{t+1}\}}\right)
\end{aligned} \tag{A.6}$$

A.2.2 Numerical solution details

The numerical dynamic programming approach considers the joint determination of the stationary equity value function (A.5) and the stationary bond pricing function (A.6). I use an iterative procedure to jointly approximate these two functions on discrete grids. Throughout the procedure, I create grids for the shocks and the endogenous state variables, $\widehat{k}_t$, $\widehat{b}_t$, and λ_t. Given their persistent nature, we use the Rouwenhorst (1995) procedure to discretize the aggregate state and the firm-level technology shocks. The aggregate Markov chain has three states and changes in the technology shock are approximated with 11 elements. I create grids for capital, the debt face value outstanding and debt maturity parameter, with 50, 10 and 10 points respectively. The choice for tomorrow's control variables is based on a dynamic searching in the original grids that consists of zooming in multiple times around local optimal values. This methodology allows the code to spend most of the processing time in a grid around the optimal value. Importantly, the procedure to find the maximum equity value function takes as given the stochastic discount factor as well as the debt pricing function. After the equity value function converges, I solve for the bond pricing function using a value function iteration procedure that takes the equity value function as given. Once this algorithm converges, I obtain the equity and bond value functions for each element on the state space.

A.2.3 Derivation of first-order conditions

Under the assumption that the firm does not need to issue equity, i.e $\Psi(\widehat{e}_t) = 0$, the set of first order necessary conditions of the original firm's problem are,

$$[\widehat{b}_{t+1}]: \ \frac{\partial \widehat{P}_t}{\partial \widehat{b}_{t+1}} \left(\widehat{b}_{t+1} - (1-\lambda_t)\widehat{b}_t e^{-\Delta \ln(x_t)}\right) + \widehat{P}_t + \mathbb{E}_t \left(M_{t,t+1} e^{\Delta \ln(x_{t+1})} \int_{\underline{z}}^{z^\star_{t+1}} \frac{\partial j_{t+1}}{\partial \widehat{b}_{t+1}} d\mathscr{Z}(z_{t+1}|z_t) \right) = 0$$

$$[\lambda_{t+1}]: \ \frac{\partial \widehat{P}_t}{\partial \lambda_{t+1}} \left(\widehat{b}_{t+1} - (1-\lambda_t)\widehat{b}_t e^{-\Delta \ln(x_t)}\right) + \mathbb{E}_t \left(M_{t,t+1} e^{\Delta \ln(x_{t+1})} \int_{\underline{z}}^{z^\star_{t+1}} \frac{\partial j_{t+1}}{\partial \lambda_{t+1}} d\mathscr{Z}(z_{t+1}|z_t) \right) = 0$$

$$[\widehat{i}_t]: \ -1 - \frac{\partial \widehat{\Phi}_t}{\partial \widehat{i}_t} + \gamma_t = 0$$

$$[\widehat{k}_{t+1}]: \ \frac{\partial \widehat{P}_t}{\partial \widehat{k}_{t+1}} \left(\widehat{b}_{t+1} - (1-\lambda_t)\widehat{b}_t e^{-\Delta \ln(x_t)}\right) - \gamma_t + \mathbb{E}_t \left(M_{t,t+1} e^{\Delta \ln(x_{t+1})} \int_{\underline{z}}^{z^\star_{t+1}} \frac{\partial j_{t+1}}{\partial \widehat{k}_{t+1}} d\mathscr{Z}(z_{t+1}|z_t) \right) = 0$$

where γ_t represents the Lagrange multiplier of the capital accumulation condition, $z^\star_{t+1}$ denotes the default threshold (the highest value of z_t at which it is optimal to keep operating the firm), and $\mathscr{Z}(\cdot)$ represents the conditional density distribution of z_{t+1}. The derivatives of the function $j(\cdot)$ can be obtained by applying the envelope theorem multiple times,

$$[\widehat{b}_t]: \ \frac{\partial j_t}{\partial \widehat{b}_t} = -(\lambda_t + c(1-\tau))e^{-\Delta \ln(x_t)} - \widehat{P}_t(1-\lambda_t)e^{-\Delta \ln(x_t)}$$

$$[\lambda_t]: \ \frac{\partial j_t}{\partial \lambda_t} = -\widehat{b}_t e^{-\Delta \ln(x_t)} + \widehat{P}_t \widehat{b}_t e^{-\Delta \ln(x_t)} = -\widehat{b}_t e^{-\Delta \ln(x_t)}(1-\widehat{P}_t) \tag{A.7}$$

$$[\widehat{k}_t]: \ \frac{\partial j_t}{\partial \widehat{k}_t} = (1-\tau)\frac{\partial \widehat{y}_t}{\partial k_t} + \tau\delta e^{-\Delta \ln(x_t)} - \frac{\partial \widehat{\Phi}_t}{\partial \widehat{k}_t} + (1-\delta)e^{-\Delta \ln(x_t)}\lambda_t$$

Note that the derivative of the debt price function can also be obtained from equation,

$$\begin{aligned}
&\widehat{b}_{t+1} \times \widehat{P}(\widehat{k}_{t+1}, \widehat{b}_{t+1}, \lambda_{t+1}, \Gamma_t) = \\
&\quad \mathbb{E}_t \Big(M_{t,t+1} \widehat{b}_{t+1} (\lambda_{t+1} + c + (1-\lambda_{t+1}) \cdot \widehat{P}(\widehat{k}_{t+2}, \widehat{b}_{t+2}, \lambda_{t+2}, \Gamma_{t+1})) \mathbb{I}_{\{z_{t+1} < z^\star_{t+1}\}} \Big) \\
&\qquad + \mathbb{E}_t \Big(M_{t,t+1} (1-\chi_{t+1}) e^{\Delta \ln(x_{t+1})} j(\widehat{k}_{t+1}, 0, 0, \Gamma_{t+1}) \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big)
\end{aligned}$$

Indeed, differentiating the debt pricing function with respect to each control variable we can completely determined the system of equations resulted from the first-order conditions of the firm's problem,

$$[\widehat{b}_{t+1}]:\ \widehat{P}_t+\widehat{b}_{t+1}\frac{\partial \widehat{P}_t}{\partial \widehat{b}_{t+1}}=\mathbb{E}_t\Big(M_{t,t+1}(1-\chi_{t+1})e^{\Delta\ln(x_{t+1})}j(\widehat{k}_{t+1},0,0,\Gamma^\star_{t+1})[-d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \widehat{b}_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(\lambda_{t+1}+c+(1-\lambda_{t+1})\cdot\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma^\star_{t+1}))[d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \widehat{b}_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}(\lambda_{t+1}+c+(1-\lambda_{t+1})\cdot\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1}))\mathbb{I}_{\{z_{t+1}<z^\star_{t+1}\}}\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(1-\lambda_{t+1})\cdot\nabla\widehat{P}^{\widehat{b}_{t+1}}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1})\mathbb{I}_{\{z_{t+1}<z^\star_{t+1}\}}\Big)$$

$$[\lambda_{t+1}]:\ \widehat{b}_{t+1}\frac{\partial \widehat{P}_t}{\partial \lambda_{t+1}}=\mathbb{E}_t\Big(M_{t,t+1}(1-\chi_{t+1})e^{\Delta\ln(x_{t+1})}j(\widehat{k}_{t+1},0,0,\Gamma^\star_{t+1})[-d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \lambda_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(\lambda_{t+1}+c+(1-\lambda_{t+1})\cdot\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma^\star_{t+1}))[d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \lambda_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(1-\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1}))\mathbb{I}_{\{z_{t+1}<z^\star_{t+1}\}}\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(1-\lambda_{t+1})\cdot\nabla\widehat{P}^{\lambda_{t+1}}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1})\mathbb{I}_{\{z_{t+1}<z^\star_{t+1}\}}\Big)$$

$$[\widehat{k}_{t+1}]:\ \widehat{b}_{t+1}\frac{\partial \widehat{P}_t}{\partial \widehat{k}_{t+1}}=\mathbb{E}_t\Big(M_{t,t+1}(1-\chi_{t+1})e^{\Delta\ln(x_{t+1})}j(\widehat{k}_{t+1},0,0,\Gamma^\star_{t+1})[-d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \widehat{k}_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(\lambda_{t+1}+c+(1-\lambda_{t+1})\cdot\widehat{P}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma^\star_{t+1}))[d\mathscr{Z}(z^\star_{t+1}|z_t)\frac{\partial z^\star_{t+1}}{\partial \widehat{k}_{t+1}}]\Big)$$
$$+\mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{t+1}(1-\lambda_{t+1})\cdot\nabla\widehat{P}^{\widehat{k}_{t+1}}(\widehat{k}_{t+2},\widehat{b}_{t+2},\lambda_{t+2},\Gamma_{t+1})\mathbb{I}_{\{z_{t+1}<z^\star_{t+1}\}}\Big)$$

where for any variable q_{t+1}, the total derivative of the debt pricing function with respect to q_{t+1} is denoted by,

$$\nabla\widehat{P}^{q_{t+1}}_{t+1}\equiv\frac{\partial\widehat{P}_{t+1}}{\partial\widehat{k}_{t+2}}\frac{\partial\widehat{k}_{t+2}}{\partial q_{t+1}}+\frac{\partial\widehat{P}_{t+1}}{\partial\widehat{b}_{t+2}}\frac{\partial\widehat{b}_{t+2}}{\partial q_{t+1}}+\frac{\partial\widehat{P}_{t+1}}{\partial\lambda_{t+2}}\frac{\partial\lambda_{t+2}}{\partial q_{t+1}}$$

A.2.4 Derivation of debt credit spreads as a function of pd and rr

The firm's creditors buy corporate debt at price $P_t\equiv P(k_{t+1},b_{t+1},\lambda_{t+1},\Gamma_t)$ in exchange of collecting coupon and principal payments until the firm defaults. If default does not occur, the bond repayment at period $t+j$ is $CF_{t+j}\equiv(1-\lambda_{t+1})^{j-1}(c+\lambda_{t+1})$. As a consequence, if the yield of the defautable bond is Y_t, then Y_t will relate to P_t according to the expression,

$$P_t=\sum_{j=1}^{\infty}\frac{CF_{t+j}}{(1+Y_t)^j}=\frac{\lambda_{t+1}+c}{\lambda_{t+1}+Y_t}\tag{A.8}$$

Similarly, if the price of a default-free debt with payments CF_{t+j} is P_t^{rf}, then the yield of the default-free bond will be computed as $Y_t^{rf} = (\lambda_{t+1} + c)/P_t^{rf} - \lambda_{t+1}$. Credit spreads ($cs_t$) is defined as the yield difference between defaultable and default-free debt,

$$cs_t \equiv Y_t - Y_t^{rf} = \frac{\lambda_{t+1} + c}{P_t} - \frac{\lambda_{t+1} + c}{P_t^{rf}} \tag{A.9}$$

To write credit spreads in terms of the probability of default PD_t and the value of the recovery rate RR_t note that P_t is defined by an arbitrage condition such that the amount of money creditors are willing to pay for the contract must equal the expected value of future payments. Formally, this condition implies the following identity,

$$\begin{aligned} P_t = \mathbb{E}_t \Big(M_{t,t+1} (\lambda_{t+1} + c + (1 - \lambda_{t+1}) P_{t+1}) \mathbb{I}_{\{z_{t+1} < z^\star_{t+1}\}} \Big) \\ + \mathbb{E}_t \Big(M_{t,t+1} (1 - \chi_{t+1}) \frac{J^0_{t+1}}{b_{t+1}} \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big) \end{aligned} \tag{A.10}$$

where J^0_{t+1} denotes the value of the unlevered firm after default, i.e. $J^0_{t+1} \equiv J(k_{t+1}, 0, 0, \Gamma_{t+1})$. Importantly, corporate bonds are held by the representative household and are thus valued using the household equilibrium pricing kernel $M_{t,t+1}$. To gain some intuition about the drivers of credit spreads, for simplicity I now consider the one-period debt case, i.e. λ_{t+1} is set to 1. For this special case, note that,

$$\frac{1+c}{P_t} = \frac{1}{\mathbb{E}_t(M_{t,t+1})} \left(\frac{1 - \mathbb{E}_t \Big(M_{t,t+1} (1 - \chi_{t+1}) \frac{J^0_{t+1}}{P_t b_{t+1}} \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big)}{1 - \mathbb{E}_t \Big(\frac{M_{t,t+1}}{\mathbb{E}_t(M_{t,t+1})} \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big)} \right) \tag{A.11}$$

similarly for the default-free bond in this special case, we have, $(1+c)/P_t = 1/\mathbb{E}_t(M_{t,t+1})$. Consequently, defining the risk-neutral default probability PD_t and the value of the recovery rate RR_t, as

$$\begin{aligned} PD_t &\equiv \mathbb{E}_t \Big(\frac{M_{t,t+1}}{\mathbb{E}_t(M_{t,t+1})} \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big) \\ RR_t &\equiv \mathbb{E}_t \Big(M_{t,t+1} (1 - \chi_{t+1}) \frac{J^0_{t+1}}{P_t b_{t+1}} \mathbb{I}_{\{z^\star_{t+1} < z_{t+1} < z^0_{t+1}\}} \Big) \end{aligned} \tag{A.12}$$

we conclude that credit spreads can be written in terms of PD_t and RR_t according,

$$cs_t(\lambda_{t+1} = 1) = \frac{1+c}{P_t} - \frac{1+c}{P_t^{rf}} = \frac{1}{\mathbb{E}_t(M_{t,t+1})} \left(\frac{1 - RR_t}{1 - PD_t} - 1 \right) \tag{A.13}$$

Note that in the general case, i.e. $\lambda_{t+1} \in [0,1]$, the credit spreads will contain an additional term related to the difference between the defaultable and default-free debt price growth. Specifically,

$$cs_t = \frac{1}{\mathbb{E}_t(M_{t,t+1})} \left(\frac{1 - RR_t - \Delta P_t}{1 - PD_t} - (1 - \Delta P_t^{rf}) \right) \tag{A.14}$$

where $\Delta P_t \equiv \mathbb{E}_t \left(M_{t,t+1}(1-\lambda_{t+1}) P_{t+1}/P_t \mathbb{I}_{\{z_{t+1} < z^{\star}_{t+1}\}} \right)$ and $\Delta P_t^{rf} \equiv \mathbb{E}_t \left(M_{t,t+1}(1-\lambda_{t+1}) P_{t+1}^{rf}/P_t^{rf} \right)$.

Table A.1: Yield data per rating category

Rating	Yield (%)	Yield Spread (bps)	N
AAA	5.01	67	477
AA+	5.04	72	274
AA	5.93	89	774
AA-	5.71	79	1581
A+	5.79	111	2333
A	5.88	118	2847
A-	6.61	133	2485
BBB+	6.46	144	2749
BBB	6.45	171	3067
Total			16587

Yield data per rating category. This table shows the sample average of corporate yields and yield spreads by credit rating. The yield spreads is obtained by subtracting from the corporate spreads, a Treasury yield with equal duration. The NAIC data's sample period is from 1995 and 2012. Yields are in percent and yield spreads are in basis points. All bonds are in U.S. dollars and have no special features (call, put, convertibility, etc.).

Table A.2: Yield data per duration category

					Yield (%)	Yield Spread (bps)	N
		duration	$<$	1yr	4.47	133	19
1yr	$\leq$	duration	$<$	2yr	4.49	113	1486
2yr	$\leq$	duration	$<$	4yr	5.26	116	3338
4yr	$\leq$	duration	$<$	6yr	6.23	119	3650
6yr	$\leq$	duration	$<$	8yr	6.5	110	2852
8yr	$\leq$	duration	$<$	10yr	6.83	154	1425
10yr	$\leq$	duration	$<$	12yr	7.07	160	2505
12yr	$\leq$	duration	$<$		6.52	126	1312
							16587

Yield data per duration category. For a detailed description of the variables, refer to Table A.1.

Table A.3: Summary statistics

Variable	Mean	Median	Sd	Min	Max
A. Bond Characteristics					
Yield (%)	6.13	6.44	1.67	0.29	19.23
Yield spreads (bps)	126	106	86	5	1489
Coupon (%)	7.23	7.2	1.33	2	11.13
Time to maturity (years)	11.02	7.39	10.64	1	100.07
Issue size (millions)	328	250	268	0.01	3250
Credit rating	A	A-	-	BBB	AAA
Z-score	2.05	1.98	0.8	-0.1	7.16
B. Firm Characteristics					
Asset Redeployability	0.32	0.34	0.09	0.09	0.58
Asset size (log millions)	9.59	9.69	1.09	6.18	12.4
Market leverage	0.23	0.24	0.14	0.01	0.68
Long-term debt to asset	0.24	0.23	0.1	0.01	0.66
Book-to-Market	0.46	0.36	0.37	0.01	5.04
Tangibility	0.4	0.34	0.22	0.03	0.93
ROA	0.16	0.15	0.06	-0.06	0.43
Tobin Q	1.99	1.66	1.14	0.69	13.01

Summary statistics. This table reports summary statistics for the benchmark sample. Panel A reports bond characteristics. Yield spreads are defined as the bond yield in excess a government bond with equal duration, coupon is the annualized coupon rate, Time to maturity is the difference between the maturity of the bond and the transaction date, the issue size is the total principal issued for a bond. Panel B reports firm characteristics, Asset redeployability computed as in Kim and Kung (2016), Asset size is defined as total assets in Compustat, Long-term debt to asset is obtained from Compustat, the Book-to-Market ratio is defined as the ratio of book equity to the market value of equity. The variable units are detailed in the first column.

Table A.4: Asset redeployability by two-digit sic

SIC	AR	Industry description	SIC	AR	Industry description
10	0.233	Metal, Mining	39	0.3574	Miscellaneous Manufacturing Ind.
13	0.1346	Oil & Gas Extraction	40	0.1425	Railroad Transportation
14	0.2898	Nonmetallic Minerals	42	0.3717	Trucking & Warehousing
20	0.3378	Food & Kindred Products	45	0.2435	Transportation by Air
21	0.3751	Tobacco Products	48	0.3465	Communications
23	0.2756	Apparel & Other Textile Prod.	50	0.4007	Wholesale Trade - Durable
25	0.3463	Furniture & Fixtures	51	0.4063	Wholesale Trade - Nondurable
26	0.2735	Paper & Allied Products	52	0.3925	Building Materials & Gardening
27	0.4297	Printing & Publishing	54	0.3925	Food Stores
28	0.3556	Chemical & Allied Products	55	0.3925	Automative dealers & Serv. Stations
29	0.3188	Petroleum & Coal Products	56	0.3922	Apparel & Accessory Stores
30	0.3526	Miscellaneous Plastics Prod.	57	0.3925	Furniture & Homefurnishings Stores
32	0.3697	Stone, Clay, & Glass Products	58	0.3694	Eating & Drinking Places
33	0.3617	Primary Metal Industries	59	0.392	Miscellaneous Retail
34	0.3641	Fabricated Metal Products	72	0.4986	Personal Services
35	0.3637	Industrial Machinery & Equip.	73	0.3387	Business Services
36	0.3551	Electronic & Other Electric Equip.	75	0.4296	Auto Repair, Services, & Parking
37	0.3064	Transportation Equipment	78	0.4087	Motion Pictures
38	0.3262	Instruments & Related Products	80	0.1289	Health Services

Asset redeployability by two-digit SIC. This table reports the average values of asset redeployability for 2-digit SIC industry. Firm-year asset redeployability are calculated as the value-weighted average of industry-level redeployability indices as in Kim and Kung (2016).

Appendix B

Appendix to Chapter 3

B.1 Data appendix

The empirical section of this chapter is based on the Compustat/CRSP merged data file. To be consistent with existing literature the sample used considers information from the first quarter in 1984 until the last quarter in 2016 from WRDS. I keep U.S incorporated firms and discard financial (SIC codes 6000-6999), utility (SIC codes 4800-4999), and quasi- government (SIC codes 9000-9999) firms. I also drop observations with missing or negative values of assets (`atq`), sales (`saleq`), and cash and short term investment securities (`cheq`). Observations that with missing liabilities (`ltq`) and observations where cash holdings are larger than assets are also eliminated. I discard firms that violate the accounting identity by more than 10%. Observations where leverage ratio is larger than the unity are eliminated as well as observations of those firms that where recorded in the database less than one year. Firms must have at least 5 observations (5 quarters) to be included into the sample. Year-to-date variables of the sale and purchase of common and preferred stock, cash dividends, and capital expenditures on the company's property, plant and equipment are converted into quarterly values.

B.1.1 Variables description

I provide the definitions of the variables used in the analysis which are conducted from the Compustat/CRSP merged data file,

– `Book Assets` : total assets (`at`)
– `Book Equity` : common/ordinary equity (`ceq`)
+ deferred tax and inv. tax credit (`txditc`)
– purchase of common and preferred stock (`pstk`)
– `Total Debt` : long-term debt (`dltt`) + short-term debt (`dlc`)
– `Book Leverage` : total debt / book assets (`at`)

- `Average Book Assets` : average of last-three years book assets
- `Debt Issuance` : Δ total debt / average book assets
- `Investment rate` : capital expenditures (`capex`) / average book assets

B.1.2 Robustness test

In this section, I reproduce Table B.1 for multiple variations of the original database used in the empirical analysis in order to verify that the results are not driven a specific subsample of the data.

As a robustness test, Table B.1 reproduces the main results of this chapter (presented in Table 3.1) including the observations from the first year a firm appears on the data base. This in order to verify if the results are robust to any IPO effect. As an additional robustness test, in Table B.2, I reproduce the analysis of this chapter from a sample where I exclude small firms, i.e. firms with total assets lower than \$10,000. Lastly, Table B.3 reproduces the main results of the chapter by redefining firms' total assets as the last-year total assets observed in the database. The main results of the chapter are robust to any of these tests.

B.2 Numerical procedure appendix

This appendix provides details regarding the solution method used to solve the quantitative model proposed in this chapter. Section B.2.1 describes the stationary version of the firm's problem. Section B.2.2 describes the Euler equations that characterized the optimal firm's decisions. Section B.2.3 describes the recursive equilibrium that characterizes the general equilibrium. Lastly, Section B.2.4 describes details of the numerical solution method implemented.

B.2.1 Shareholders' stationary problem

Defining the stationary variables: $\widehat{k}_{j,t+1} \equiv k_{j,t+1}/e^{x_t}$, $\widehat{i}_{j,t} \equiv i_{j,t}/e^{x_{t-1}}$, and $\widehat{b}_{j,t+1} \equiv b_{j,t+1}/e^{x_t}$; the stationary value function $J(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t)/e^{x_{t-1}} \equiv \widehat{J}(\widehat{k}_{j,t}, \widehat{b}_{j,t}, z_{j,t}, \Gamma_t)$ can be written as,

$$\widehat{J}(\widehat{k}_{j,t}, \widehat{b}_{j,t}, z_{j,t}, \Gamma_t) = \max_{\widehat{k}_{j,t+1}, \widehat{b}_{j,t+1}} \left\{ \widehat{d}_{j,t} + \mathbb{E}_t (M_{t,t+1} e^{\Delta x_t} \widehat{J}(\widehat{k}_{j,t+1}, \widehat{b}_{j,t+1}, z_{j,t+1}, \Gamma_{t+1})) \right\} \tag{B.1}$$

where the stationary functions used to solve the program are,

$$\begin{aligned}
\widehat{d}_{j,t} &\equiv \widehat{e}_{j,t} - \psi_1 \mathbb{I}_{\{\widehat{e}_{j,t}<0\}} \\
\widehat{e}_{j,t} &\equiv (1-\tau)\widehat{\Pi}_{j,t} - \widehat{i}_{j,t} - \widehat{\Omega}^k(\widehat{i}_{j,t}) - (\lambda + c(1-\tau))\widehat{b}_{j,t} + \tau\delta\widehat{k}_{j,t} - \widehat{\Omega}^b(\widehat{a}_{j,t}) \\
&\qquad + P(\widehat{k}_{j,t+1}, \widehat{b}_{j,t+1}, z_{j,t}, \Gamma_t)\left(\widehat{b}_{j,t+1} e^{\Delta x_t} - (1-\lambda)\widehat{b}_{j,t}\right) \\
\widehat{y}_{j,t} &\equiv e^{\Delta x_t} e^{z_{j,t}} \widehat{k}_{j,t}^{\alpha} l_{j,t}^{\widehat{\alpha}} - \widehat{w}_t l_{j,t} - f\widehat{k}_{j,t} \\
\widehat{i}_{j,t} &\equiv \widehat{k}_{t+1} e^{\Delta x_t} - (1-\delta) k_t
\end{aligned}$$

Note that the debt pricing function can also be normalized,

$$\widehat{b}_{j,t+1} \times \widehat{P}_{j,t} = \mathbb{E}_t\Big(M_{t,t+1}\widehat{b}_{j,t+1}(\lambda + c + (1-\lambda)\cdot\widehat{P}_{j,t+1})\mathbb{I}_{\{z_{j,t+1}<z^\star_{j,t+1}\}}\Big) \\ + \mathbb{E}_t\Big(M_{t,t+1}(1-\chi)\widehat{J}(\widehat{k}_{j,t+1},0,z_{j,t+1},\Gamma_{t+1})\mathbb{I}_{\{z^\star_{j,t+1}<z_{j,t+1}<z^0_{j,t+1}\}}\Big) \tag{B.2}$$

B.2.2 Derivation of first-order conditions

Assuming that the firm does not need to issue equity, i.e $\psi_e \times \mathbb{I}_{\{e_{j,t}<0\}} = 0$, the set of first order conditions that determines the optimal firms' decisions are,

$$[b_{j,t+1}]: \;\; \frac{\partial P_{j,t}}{\partial b_{j,t+1}}(b_{j,t+1}-(1-\lambda)b_{j,t}) + P_{j,t} + \mathbb{E}_t\left(M_{t,t+1}\int_{z^\star_{j,t+1}}^{\bar{z}} \frac{\partial J_{j,t+1}}{\partial b_{j,t+1}} d\mathscr{Z}(z_{j,t+1}|z_{j,t})\right) = \frac{\partial\Omega^b(a_{j,t})}{\partial a_{j,t}}$$

$$[i_{j,t}]: \;\; -1 - \frac{\partial\Omega^k(i_{j,t})}{\partial i_{j,t}} + \gamma_{j,t} = 0$$

$$[k_{j,t+1}]: \;\; \frac{\partial P_{j,t}}{\partial k_{j,t+1}}(b_{j,t+1}-(1-\lambda)b_{j,t}) - \gamma_{j,t} + \mathbb{E}_t\left(M_{t,t+1}\int_{z^\star_{j,t+1}}^{\bar{z}} \frac{\partial J_{j,t+1}}{\partial k_{j,t+1}} d\mathscr{Z}(z_{j,t+1}|z_{j,t})\right) = 0$$

where $\gamma_{j,t}$ represents the Lagrange multiplier of the capital accumulation condition, $z^\star_{j,t+1}$ denotes the default threshold (the lowest value of $z_{j,t+1}$ at which it is optimal to keep operating the firm), and $\mathscr{Z}(\cdot)$ represents the conditional density distribution of $z_{j,t+1}$. The derivatives of the function $J(\cdot)$ can be obtained by applying the envelope theorem multiple times,

$$[b_{j,t}]: \;\; \frac{\partial J_{j,t}}{\partial b_{j,t}} = -(\lambda + c(1-\tau)) - P_{j,t}(1-\lambda) + \frac{\partial\Omega^b(a_{j,t})}{\partial b_{j,t}}(1-\lambda) \\ [k_{j,t}]: \;\; \frac{\partial J_{j,t}}{\partial k_{j,t}} = (1-\tau)\frac{\partial y_{j,t}}{\partial k_{j,t}} + \tau\delta - \frac{\partial\Omega^k(i_{j,t})}{\partial k_{j,t}} + (1-\delta)\gamma_{j,t} \tag{B.3}$$

Note that the derivative of the debt price function can also be obtained from equation,

$$b_{j,t+1} \times P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t) = \\ \mathbb{E}_t\Big(M_{t,t+1}b_{j,t+1}(\lambda + c + (1-\lambda)\cdot P(k_{j,t+2}, b_{j,t+2}, z_{j,t+1}, \Gamma_{t+1}))\mathbb{I}_{\{z^\star_{j,t+1}<z_{j,t+1}\}}\Big) \\ + \mathbb{E}_t\Big(M_{t,t+1}(1-\chi)J(k_{j,t+1},0,z_{j,t+1},\Gamma_{t+1})\mathbb{I}_{\{z^0_{j,t+1}<z_{j,t+1}<z^\star_{j,t+1}\}}\Big)$$

Finally, by differentiating the debt pricing function with respect to each control variable, the system of equations resulted from the first-order conditions is completely determined,

$$
\begin{aligned}
[b_{j,t+1}]:\ \ P_{j,t}+b_{j,t+1}\frac{\partial P_{j,t}}{\partial b_{j,t+1}} &= \mathbb{E}_t\Big(M_{t,t+1}(1-\chi)J(k_{j,t+1},0,z^{\star}_{j,t+1},\Gamma_{t+1})[d\mathscr{Z}(z^{\star}_{j,t+1}|z_{j,t})\frac{\partial z^{\star}_{j,t+1}}{\partial b_{j,t+1}}]\Big)\\
&+\mathbb{E}_t\Big(M_{t,t+1}b_{j,t+1}(\lambda+c+(1-\lambda)\cdot P(k_{j,t+2},b_{j,t+2},z^{\star}_{j,t+1},\Gamma_{t+1}))[-d\mathscr{Z}(z^{\star}_{j,t+1}|z_{j,t})\frac{\partial z^{\star}_{j,t+1}}{\partial b_{j,t+1}}]\Big)\\
&+\mathbb{E}_t\Big(M_{t,t+1}(\lambda+c+(1-\lambda)\cdot P(k_{j,t+2},b_{j,t+2},z_{j,t+1},\Gamma_{t+1}))\mathbb{I}_{\{z^{\star}_{j,t+1}<z_{j,t+1}\}}\Big)\\
&+\mathbb{E}_t\Big(M_{t,t+1}b_{j,t+1}(1-\lambda)\cdot\nabla P^{b_{j,t+1}}(k_{j,t+2},b_{j,t+2},z_{j,t+1},\Gamma_{t+1})\mathbb{I}_{\{z^{\star}_{j,t+1}<z_{j,t+1}\}}\Big)
\end{aligned}
$$

$$
\begin{aligned}
[k_{j,t+1}]:\quad b_{j,t+1}\frac{\partial P_{j,t}}{\partial k_{j,t+1}} &= \mathbb{E}_t\Big(M_{t,t+1}(1-\chi)J(k_{j,t+1},0,z^{\star}_{j,t+1},\Gamma_{t+1})[d\mathscr{Z}(z^{\star}_{j,t+1}|z_{j,t})\frac{\partial z^{\star}_{j,t+1}}{\partial k_{j,t+1}}]\Big)\\
&+\mathbb{E}_t\Big(M_{t,t+1}b_{j,t+1}(\lambda+c+(1-\lambda)\cdot P(k_{j,t+2},b_{j,t+2},z^{\star}_{j,t+1},\Gamma_{t+1}))[-d\mathscr{Z}(z^{\star}_{j,t+1}|z_{j,t})\frac{\partial z^{\star}_{j,t+1}}{\partial k_{j,t+1}}]\Big)\\
&+\mathbb{E}_t\Big(M_{t,t+1}b_{j,t+1}(1-\lambda)\cdot\nabla P^{k_{j,t+1}}(k_{j,t+2},b_{j,t+2},z_{j,t+1},\Gamma_{t+1})\mathbb{I}_{\{z^{\star}_{j,t+1}<z_{j,t+1}\}}\Big)
\end{aligned}
$$

where for any variable q_{t+1}, the total derivative of the debt pricing function with respect to q_{t+1} represents the expression,

$$
\nabla P^{q_{j,t+1}}_{t+1} \equiv \frac{\partial P_{j,t+1}}{\partial k_{j,t+2}}\times\frac{\partial k_{j,t+2}}{\partial q_{t+1}} + \frac{\partial P_{j,t+1}}{\partial b_{j,t+2}}\times\frac{\partial b_{j,t+2}}{\partial q_{t+1}}
$$

B.2.3 Recursive equilibrium

The recursive equilibrium consists of a set of value functions, prices, household' and firms' optimal decisions, aggregate quantities and the law of motion of the economy's aggregate state satisfying the following set of conditions.

Policy and Value Functions

1. Firm j-th's policy functions $\{k^*_{j,t+1}, l^*_{j,t}, b^*_{j,t+1}\}$ maximize its value function $J(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t)$.
2. Household's optimal decisions $C^*(\{m^s_{j,t}\}, m^b_t, \Gamma_t)$, $N^*(\{m^s_{j,t}\}, m^b_t; \Gamma_t)$, $m^{s*}(\{m^s_{j,t}\}, m^b_t, \Gamma_t)$, and $m^{b*}(\{m^s_{j,t}\}, m^b_t, \Gamma_t)$ maximize $H(\{m^s_{j,t}\}, m^b_t, \Gamma_t)$.
3. $m^{s*}_{j,t+1} \equiv m^{s*}(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t) = \mu_{t+1}(k_{j,t+1}, b_{j,t+1} z_{j,t}, \Gamma_t)\ \ \forall (k_{j,t+1}, b_{j,t+1} z_{j,t}) \in S$.

Market Clearing Conditions

1. Commodity market clearing, $C(\Gamma_t) = Y(\Gamma_t) - \Theta(\Gamma_t)$; where,
   (a) $Y(\Gamma_t) = \int_S e^{(1-\alpha)x_t} e^{z_{j,t}} (k_{j,t})^{\alpha} (l^*_{j,t})^{1-\widehat{\alpha}} \mu_t[d(k_{j,t} \times b_{j,t} \times z_{j,t})]$.

(b) $\Theta(\Gamma_t) = \int_S \left[f \times k_{j,t} + i^*_{j,t} + \Omega^k(i^*_{j,t}) + \Omega^b(a^*_{j,t}) + \psi_e \mathbb{I}_{\{e_{j,t}<0\}} \right] \mu_t[d(k_{j,t} \times b_{j,t} \times z_{j,t})]$.

where $i^*_{j,t} \equiv k^*_{j,t+1} - (1-\delta)k_{j,t}$, and $a^*_{j,t} \equiv b^*_{j,t+1} - (1-\lambda)b_{j,t}$.

2. Labor market clearing, $N^*(\Gamma_t) = \int_S l^*(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t)\, \mu_t[d(k_{j,t} \times b_{j,t} \times z_{j,t})]$.

3. The bond market clearing condition, is satisfied by Walras' Law and the assumption that the representative financial intermediary participates in a competitive market.[1]

Model's consistent dynamic

1. Law of motion for aggregate state variables $\Gamma_t = \mu_{t+1}$ is consistent with agents' decisions. Formally, $\mu_{t+1}(\mathscr{K}, \mathscr{B}, \mathscr{Z}) = \int_{(k_{j,t}, b_{j,t}, z_{j,t}) \in \mathscr{S}} \left[\sum_{z_{j,t+1} \in \mathscr{Z}} \Pi^{(z)}_{(z_{j,t}, z_{j,t+1})} \right] \mu_t[d(k_{j,t} \times b_{j,t} \times z_{j,t})]$; for all $(\mathscr{K}, \mathscr{B}, \mathscr{Z}) \subset \mathscr{S} \equiv \{(k_{j,t}, b_{j,t}, z_{j,t}) \mid k'^*(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) \in \mathscr{K}$ and $b^*_{j,t+1}(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) \in \mathscr{B}\}$; and where $\Pi^{(z)}$ denotes the transition probability of $z_{j,t}$.

Aggregate Prices

1. The stochastic discount factor satisfies, $M_{t,t+1} = \beta \left(\frac{H^{1-\gamma}_{t+1}}{\mathbb{E}_t\left(H^{1-\gamma}_{t+1}\right)} \right)^{\frac{1/\psi - \gamma}{1-\gamma}} \left(\frac{\widehat{C}_{t+1}}{\widehat{C}_t} \right)^{-\frac{1}{\psi}} \frac{\partial \widehat{C}_{t+1}/\partial C_{t+1}}{\partial \widehat{C}_t/\partial C_t}$; where $H_{t+1} \equiv H(C(\Gamma_{t+1}), N(\Gamma_{t+1}))$ and $\widehat{C}_{t+1} \equiv \widehat{C}(C(\Gamma_{t+1}), N(\Gamma_{t+1}))$.

2. The aggregate wage equals the household marginal rate of substitution between leisure and consumption, i.e. $w_t(\Gamma_t) = -\left({}^{\partial \widehat{C}_t}/_{\partial N_t} \right) \left({}^{\partial \widehat{C}_t}/_{\partial C_t} \right)^{-1}$.

B.2.4 Numerical solution details

The numerical dynamic programming approach considers the joint determination of (i) the stationary equity value function (B.1), (ii) the stationary bond pricing function (B.2), and (iii) the functions for aggregate consumption and aggregate wages (aggregate beliefs) that firms use to solve their maximization problem. I use an iterative procedure to jointly approximate these functions on discrete

[1]Indeed, the assumption that the representative financial intermediary participates in a competitive market implies the following zero-profit condition that is satisfied at each period,

$$
\begin{aligned}
0 \equiv P_f(\Gamma_t) \times m^b_{t+1} - &\int_S b_{j,t+1}(k_{j,t}, b_{j,t}, z_{j,t}, \Gamma_t) \times P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t) \mu_t(d(k_{j,t} \times b_{j,t} \times z_{j,t})) \\
&+ \int_{S^*} \left[b_{j,t}(1-\lambda) \times P(k_{j,t+1}, b_{j,t+1}, z_{j,t}, \Gamma_t) + b_{j,t}(\lambda + c) \right] \mu_t(d(k_{j,t} \times b_{j,t} \times z_{j,t})) \\
&\qquad + \int_{S^D} (1-\chi) J(k_{j,t}, 0, z_{j,t}, \Gamma_t) \mu_t(d(k_{j,t} \times b_{j,t} \times z_{j,t})) - m^b_t
\end{aligned}
$$

where the space S represents the product space $\mathbb{R}^+ \times \mathbb{R}^+ \times \mathscr{Z}$; where $\mathscr{Z}$ denotes the space of the idiosyncratic technology shock $z_{i,j}$. The space S^* and S^D denote the product space that includes solvent and defaulting firms, respectively. Formally, $S^D \equiv = S - S^* = S \cap (S^*)'$.

grids. Throughout the procedure, I create grids for the variables representing shocks and the endogenous state variables such as capital, and debt outstanding.

For the aggregate shocks, $(\Delta x_t, s_t)$, I use a Rouwenhorst (1995) procedure to discretize the firm-level technology shocks. The aggregate Markov chain considers five states for Δx_t and five states for s_t. Whereas the idiosyncratic technology shock is approximated with 19 points in the grid. I create grids for capital and the debt face value outstanding, with 50 and 30 points respectively. The choice for next-period control variables is based on a dynamic searching over the original grids. Specifically, in each iteration of the value function procedure, I zoom in multiple times around local optimal values of capital and debt. This methodology allows the code to spend most of the processing time in a grid around the optimal value.

The procedure to find the maximum equity value function takes as given the stochastic discount factor, the debt pricing function as well as aggregate beliefs. After the equity value function converges, I solve for the bond pricing function using a value function iteration procedure that takes the equity value function as given. Having the firms' decisions determined, firms' beliefs about aggregate variables (e.g. aggregate consumption and wage) are updated using the model's simulations. These beliefs are used by firms to compute the stochastic discount factor used to solve their maximization problem. Importantly, in this procedure instead of assuming specific functional forms for these beliefs, I follow a non-parametric approach where beliefs are estimated for each element of the aggregate state space. Finally, I use the change of the estimation of these beliefs as a metric to determine the convergence of the entire numerical solution.

Table B.1: Moments and statistics of the cross-sectional distribution of debt issuance and investment rate (excluding small firms)

Panel A	debt issuance			investment rate		
moments of firm-level distr.:	average	$\rho(\cdot,\text{hp-Y})$		average	$\rho(\cdot,\text{hp-Y})$	
mean	0.004	0.54	**	0.017	0.63	***
fraction of firms with $(-)$ spikes	0.058	-0.42	**	0.001	0.02	
fraction of firms with $(+)$ spikes	0.079	0.61	***	0.051	0.59	***
standard deviation	0.059	0.48	**	0.021	0.56	**
Panel B		$\rho(\cdot,\text{C-S st.dev.})$			$\rho(\cdot,\text{C-S st.dev.})$	
fraction of firms with $(-)$ spikes		-0.31	**		0.03	
fraction of firms with $(+)$ spikes		0.86	***		0.95	***
Panel C	average	$\rho(\cdot,\text{C-S st.dev.})$			$\rho(\cdot,\text{C-S st.dev.})$	
fraction of firms with:						
$(+)$ debt issuance spikes	0.079	0.86	***		0.73	***
$(+)$ investment spikes	0.051	0.68	***		0.95	***
$(+)$ debt issuance spikes, and no-$(+)$ investment spikes	0.064	0.81	***		0.61	***
no-$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.036	0.56	**		0.89	***
$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.014	0.77	***		0.89	***

Moments and statistics of the cross-sectional distribution of debt issuance and investment rate (excluding small firms). This table shows some empirical facts about the business dynamic of the cross-sectional distribution of debt issuance and investment rates when firms with total asset lower than \$10,000 are excluded from the sample. Refer to Table 3.1 for details about variables' definitions.

Table B.2: Moments and statistics of the cross-sectional distribution of debt issuance and investment ratio (ipo firms)

Panel A	debt issuance			investment rate		
moments of firm-level distr.:	average	$\rho(\cdot,$hp-Y$)$		average	$\rho(\cdot,$hp-Y$)$	
mean	0.003	0.59	***	0.017	0.63	***
fraction of firms with $(-)$ spikes	0.062	-0.46	**	0.001	0.02	
fraction of firms with $(+)$ spikes	0.078	0.63	***	0.046	0.61	***
standard deviation	0.062	0.48	**	0.022	0.56	**
Panel B		$\rho(\cdot,$C-S st.dev.$)$			$\rho(\cdot,$C-S st.dev.$)$	
fraction of firms with $(-)$ spikes		-0.21	*		0.03	
fraction of firms with $(+)$ spikes		0.86	***		0.95	***
Panel C	average	$\rho(\cdot,$C-S st.dev.$)$			$\rho(\cdot,$C-S st.dev.$)$	
fraction of firms with:						
$(+)$ debt issuance spikes	0.078	0.83	***		0.71	***
$(+)$ investment spikes	0.046	0.65	***		0.95	***
$(+)$ debt issuance spikes, and no-$(+)$ investment spikes	0.061	0.79	***		0.58	***
no-$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.033	0.52	**		0.87	***
$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.013	0.75	***		0.89	***

Moments and statistics of the cross-sectional distribution of debt issuance and investment rate (IPO firms). This table shows some empirical facts about the business dynamic of the cross-sectional distribution of debt issuance and investment rates when the first year from each firm's time series is included in the sample. Refer to Table 3.1 for details about variables' definitions.

Table B.3: Moments and statistics of the cross-sectional distribution of debt issuance and investment ratio (total assets redefined)

Panel A	debt issuance			investment rate		
moments of firm-level distr.:	average	$\rho(\cdot,\text{hp-Y})$		average	$\rho(\cdot,\text{hp-Y})$	
mean	0.004	0.56	**	0.016	0.64	***
fraction of firms with $(-)$ spikes	0.076	-0.54	**	0.001	0.02	
fraction of firms with $(+)$ spikes	0.105	0.52	**	0.059	0.61	***
standard deviation	0.059	0.31	**	0.021	0.58	***
Panel B		$\rho(\cdot,\text{C-S st.dev.})$			$\rho(\cdot,\text{C-S st.dev.})$	
fraction of firms with $(-)$ spikes		-0.32	**		0.03	
fraction of firms with $(+)$ spikes		0.81	***		0.97	***
Panel C	average	$\rho(\cdot,\text{C-S st.dev.})$			$\rho(\cdot,\text{C-S st.dev.})$	
fraction of firms with:						
$(+)$ debt issuance spikes	0.105	0.81	***		0.73	***
$(+)$ investment spikes	0.059	0.59	***		0.97	***
$(+)$ debt issuance spikes, and no-$(+)$ investment spikes	0.088	0.81	***		0.66	***
no-$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.042	0.47	**		0.93	***
$(+)$ debt issuance spikes, and $(+)$ investment spikes	0.017	0.71	***		0.87	***

Moments and statistics of the cross-sectional distribution of debt issuance and investment rate (total assets redefined). This table shows some empirical facts about the business dynamic of the cross-sectional distribution of debt issuance and investment rates for the case where total assets are computed as last-year assets. Refer to Table 3.1 for details about variables' definitions.