# Investment-Based Corporate Bond Pricing*

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**Abstract**

A key shortcoming of structural models of default is that they specify the evolution of the firm's asset value exogenously. Debt is used to fund changes in equity but it does not affect the asset side of the balance sheet. Empirically, however, firms use debt primarily to finance capital spending. In this paper, we document the importance of accounting for investment options in models of credit risk. In the presence of financing and investment frictions, firm-level variables which proxy for asset composition carry explanatory power for credit spreads beyond leverage. As a result, we suggest that cross-sectional studies of credit spreads and default probabilities that fail to control for the interdependence of leverage and investment decisions are unlikely to be very informative. Quantitatively, we show how to obtain a realistic term structure of credit spreads in a production economy.

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# 1 Introduction

Quantitative research on credit risk has derived much of its intuition from models in the tradition of Merton (1974) and Leland (1994). In these structural models of credit risk, firms optimally choose to default when the present value of coupon payments to bond holders is greater than the present value of future dividends. This optimality condition also provides testable implications for the relation between firm-level variables and credit spreads. For instance, leverage should be positively related to credit spreads since higher leverage implies the firm is closer to the default boundary. However, the empirical evidence is mixed; for example, Collin-Dufresne, Goldstein, and Martin (2001) show that structural models explain less than 25 percent of the variation in credit spread changes.[1]

A key feature of current structural models of default is that they specify the evolution of the firm's asset value exogenously. Typically, when choosing their leverage, firms trade off tax benefits of debt and bankruptcy costs. Given that assets evolve exogenously, the issued debt is used to fund changes in equity but it does not affect the asset side of the balance sheet. Empirically, however, firms use debt primarily to finance capital spending. In this paper, we document the importance of accounting for investment decisions in models of credit risk. Exercising investment options changes a firm's asset composition and hence the riskiness of its assets. In a world with financial market imperfections, default probabilities and hence credit spreads will reflect the riskiness of firms' assets. Our results suggest that these effects are quantitatively significant.

While we build on the recent literature relating firms' capital structures to their investment policies (Hennessy and Whited (2005, 2007)), we introduce Epstein-Zin preferences with time varying macroeconomic risk in consumption and productivity in a cross-sectional production economy to price risky corporate debt.[2] In the model, firms possess the option to expand capacity. Investment can be financed with retained earnings, equity or debt issuances. In contrast to corporate models of default, such as Leland (1994), where the tax advantage of debt leads firms to issue debt, it is the availability of real investment options in our model. We assume debt takes the form of one period debt and firms choose jointly optimal leverage and investment to maximize equity value. Importantly, firms can default on their outstanding

[1]Similarly, Davydenko and Strebulaev (2007) reach a similar conclusion for the level of credit spreads.

[2]Similar to Bansal and Yaron (2004), we model time varying macroeconomic risk as a mean reverting process in the first and second moments of consumption growth.

debt when the option to default is more valuable than paying back bond holders. When making these dynamics decisions, firms face fix and proportional debt and equity issuances costs.

Our paper makes three sets of contributions. First, we provide new testable implications concerning the firm-level determinants of credit spreads. Our models predicts that suitable empirical proxies for growth options should have considerable explanatory power for credit spreads and their changes, an implication not shared by standard structural models of credit risk. Specifically, the market-to-book ratio or investment rate are important determinants of credit spreads in our model. This is because they capture information about the composition and riskiness of firms' assets. While in a world without real and financial imperfections leverage would perfectly adjust to reflect the riskiness of assets, empirically leverage often deviates substantially from target leverage (Leary and Roberts (2005), Strebulaev (2007)). In such a realistic setting, proxies for asset composition should carry explanatory power for credit spreads beyond leverage. We confirm and quantify this prediction by means of cross-sectional regressions in our model. As credit spreads reflect default probabilities, an analogous implication holds for logit regressions of expected default rates.

Second, we demonstrate that the link between firm-level characteristics and credit risk depends on macroeconomic conditions in a model with investment options. Intuitively, as growth options pay off in good times, growth firms have more volatile cash flows and are thus riskier than value firms which derive most of their value from assets in place. For the same amount of debt, growth firms have higher default rates than value firms in good times. However, growth firms choose optimally lower leverage than value firms in the model and the data, rendering the link between leverage and credit spreads uninformative. In contrast, value firms are more risky than growth firms in bad times because of operating leverage. Value firms have excess capital and debt and thus higher default rates than growth firms. As a result, the relation between the market-to-book ratio and credit spreads is positive in booms and negative in recessions, holding leverage constant. Moreover, the link between leverage and credit spreads is only strong in bad times. These subtle conditional links therefore make the unconditional relationship quite uninformative. Consequently, the relationship between credit spreads and firm-level characteristics depends on the the availability of growth options as well as macroeconomic conditions. This demonstrates the importance of accounting for the endogeneity of both investment and financing when explaining credit spreads. We show that in such an environment the weak empirical performance of firm-level variables in unconditional tests obtains naturally.

Third, our model quantitatively rationalizes the empirical term structure of credit spreads in a production economy. As pointed out by Huang and Huang (2003), standard models of credit risk, such as Merton (1974) and Leland (1994), are not able to generate a realistic spread of risky debt relative to safe governments bonds. While, as demonstrated by several authors (Hackbarth, Miao, and Morellec (2006), Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010)), substantial credit risk premia as compensation for macroeconomic conditions go a long way towards explaining the credit spread puzzle in endowment economics, production economies place considerably tighter restrictions on this link. Jermann (1998) and Kogan (2004) point out that explaining risk premia in production economies is much more challenging than in an endowment economy since the agent can use capital to smooth cash flows.

Quantitatively, our model generates a realistic credit spread of 101 basis points for 5 year debt and 114 basis points for 10 year debt for BBB firms, close to empirical estimates. At the same time, actual default probabilities are low as in the data. The reason for success is twofold. First, we assume that capital is firm specific and thus the resale value is zero. In a model without disinvestment costs, firms would rarely choose to default because firms would sell capital to pay off their debt. Essentially, the value of the disinvestment option drives out the value of the default option. Second, we measure credit spreads in the cross section of firms as in Bhamra, Kuehn, and Strebulaev (2010). The standard approach is to measure credit spreads when firms issue new debt. In reality, however, firms adjust leverage only infrequently as shown by Leary and Roberts (2005). Cross-sectional heterogeneity in asset composition and leverage raise the average credit spread because the value of both the investment and default option are convex functions of the state variables.

## Related Literature

Our paper is at the center of several converging lines of literature. First of all, our objective is to link structural models of default and financing and the literature on growth options and firm investment. In this regard, our paper is related to Miao (2005), Sundaresan and Wang

(2007) and Bolton, Chen, and Wang (2010). Contrary to our work, these papers do not focus on the pricing of corporate bonds, and do not consider the importance of macroeconomic conditions.

In this regard, our paper is related to recent work using dynamic models of leverage to price corporate bonds (Hackbarth, Miao, and Morellec (2006), Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010)). Motivated by the credit spread puzzle, the observation pointed out by Huang and Huang (2003) that standard structural models of corporate finance in the tradition of Merton are unable to rationalize the historical levels of credit spreads, this literature has stressed the importance of accounting for macroeconomic risk in explaining corporate bond prices. We add to this literature by explicitly considering the role of investment in determining corporations' financing needs and policies. While the extant literature considered endowment economies only, our analysis stresses that frictions to adjusting firms' assets are a crucial determinant of default decisions, and therefore credit spreads.

More broadly, a growing literature attempts to quantitatively understand firm level investment by linking it to corporate financial policies in settings with financial frictions. While early influential work (see for instance Gilchrist and Himmelberg (1995) and Gomes (2001)) was motivated by the cash-flow sensitivity of corporate investment and considered reduced form representations of the costs of external finance, more recently the literature has considered full fledged capital structure choices, allowing for leverage, default and equity issuance (a partial list includes Cooley and Quadrini (2001), Moyen (2004), Hennessy and Whited (2005) and Hennessy and Whited (2007)). These papers suggest that in the presence of financial frictions, the availability and pricing of external funds is a major determinant of corporate investment. The novelty in our work is the analysis of the role of macroeconomic risk for corporations' investment and financing policies. In particular, while the extant literature has considered settings without aggregate risk, we stress its importance in generating the observed levels and dynamics of the costs of debt. Specifically, our model is consistent with the fact that a large fraction of both level and time-variation of credit spreads is accounted for by risk premia.

Our work is also related to a growing literature on dynamic quantitative models investigating the implications of firms' policies on asset returns. A number of papers (a partial list includes Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004) and Zhang (2005)) has successfully related anomalies in the cross section of stock returns such as the value premium to firms' investment policies. Another recent line of research has focused on the link between firms' financing decisions and stock returns (some recent papers include Garlappi and Yan (2008), Livdan, Sapriza, and Zhang (2009) and Gomes and Schmid (2009)). By relating risk premia in corporate bond prices to firms' investment and financing policies, our work here is complementary. Moreover, from a methodological point of view, we add a long run risk perspective to the literature on the cross-section of stock returns by providing a tractable way of modeling firms' exposure to long run movements in aggregate consumption growth in the sense of Bansal and Yaron (2004).

More generally, the paper adds to the broad literature on dynamic models of firms' debt policies subject to transaction costs along the lines of Fischer, Heinkel, and Zechner (1989), Leland (1994), Goldstein, Ju, and Leland (2001) and Strebulaev (2007). Here the novelty in our work is the endogeneity of investment and we provide an analysis of both financial and real transaction costs.

More recently, Chen and Manso (2010) and Arnold, Wagner, and Westermann (2011) also explore the effects of growth options on credit risk. A limitation of both models is that firms have an infinite amount of cash on hand to finance real options. In contrast, firms face an intratemporal budget constraint in our model which gives rise to a richer set of implications.

# 2 Model

In this section, we first derive the pricing kernel of the representative agent. We assume the representative agent has recursive preferences and the conditional first and second moments of consumption growth are time varying and follow a persistent Markov chain. An important implication of recursive preferences is that the agent is averse to intertemporal risk coming from the Markov chain. These assumptions give rise to realistic level and dynamics for the market price of risk.

In the second subsection, we describe the firm's problem. Firms choose optimal investments to maximize their equity value. Investments are financed by retained earnings as well as equity or debt issuances. Firms can default on their outstanding debt if prospects are sufficiently bad.

## 2.1 Pricing Kernel

The representative agent maximizes recursive utility, $U_t$, over consumption following Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1989), given by

$$U_t = \left\{(1-\beta)C_t^\rho + \beta\left(\mathbb{E}_t[U_{t+1}^{1-\gamma}]\right)^{\rho/(1-\gamma)}\right\}^{1/\rho} \tag{1}$$

where $C_t$ denotes consumption, $\beta \in (0,1)$ the rate of time preference, $\rho = 1 - 1/\psi$ and $\psi$ the elasticity of intertemporal substitution (EIS), and $\gamma$ relative risk aversion (RRA). Implicit in the utility function (1) is a constant elasticity of substitution (CES) time aggregator and CES power utility certainty equivalent.

Epstein-Zin preferences provide a separation between the elasticity of intertemporal substitution and relative risk aversion. These two concepts are inversely related when the agent has power utility. Intuitively, the EIS measures the agents willingness to postpone consumption over time, a notion well-defined under certainty. Relative risk aversion measures the agents aversion to atemporal risk across states. Recursive preferences also imply preference for either early or late resolution of uncertainty which are crucial for the quantitative implications of this paper.

We assume that aggregate consumption follows a random walk with a time-varying drift and volatility

$$C_{t+1} = C_t \exp\{g + \mu_c(s_t) + \sigma_c(s_t)\eta_{t+1}\} \tag{2}$$

where $\mu(s_t)$ and $\sigma(s_t)$ depend on the aggregate state of the economy denoted by $s_t$ and $\eta_{t+1}$ are i.i.d. standard normal innovations. The aggregate state, $s_t$, follows a persistent Markov chain with transition matrix $P$.

The Epstein-Zin pricing kernel is given by

$$M_{t,t+1} = \beta^\theta \left(\frac{C_{t+1}}{C_t}\right)^{-\gamma} \left(\frac{Z_{t+1}+1}{Z_t}\right)^{-(1-\theta)} \tag{3}$$

where $Z_t$ denotes the wealth-consumption ratio and $\theta = \frac{1-\gamma}{1-1/\psi}$. When $\theta = 1$, the pricing kernel reduces to the one generated by a representative agent with power utility, implying that she is indifferent with respect to intertemporal macroeconomic risk. When the EIS is greater than the inverse of relative risk aversion ($\psi > 1/\gamma$), the agent prefers intertemporal risk due to the Markov chain to be resolved sooner rather than later.

A economy which is solely driven by i.i.d. shocks, the wealth-consumption ratio is constant. In our model, however, the first and second moments of consumption growth follow a Markov chain. Consequently, the wealth-consumption ratio is a function of the state of the economy, i.e., $Z_t = Z(s_t)$. Based on the Euler equation for the return on wealth, the wealth-consumption ratio vector $Z_t$ solves the system of nonlinear equations defined by

$$Z_t^{\theta} = \mathbb{E}_t \left[ \beta^{\theta} \left( \frac{C_{t+1}}{C_t} \right)^{1-\gamma} (Z_{t+1} + 1)^{\theta} \right] \tag{4}$$

To compute credit spreads, we define the $n$-period risk-rate as $R_{f,t}^{(n)} = 1/\mathbb{E}_t[M_{t,t+n}]$.

## 2.2 Profits and Investment

We begin by considering the problem of a typical value maximizing firm in a perfectly competitive environment. The flow of after tax operating profits, $\Pi$, for firm $i$ is described by the expression

$$\Pi_{i,t} = (1 - \tau)(X_{i,t}^{1-\alpha} K_{i,t}^{\alpha} - K_{i,t} f) \tag{5}$$

where $X_{i,t}$ is a productivity shock and $K_{i,t}$ denotes the book value of the firm's assets. We use $\tau$ to denote the corporate tax rate, $0 < \alpha < 1$ the capital share of production and $f \geq 0$ proportional costs of production.

The $i$-th firm productivity shock follows a random walk with a time-varying drift and volatility

$$X_{i,t+1} = X_{i,t} \exp\{g + \mu_x(s_t) + \sigma_x(s_t)\varepsilon_{i,t+1}\} \tag{6}$$

where $\mu^x(s_t)$ and $\sigma^x(s_t)$ depend on the aggregate state of the economy and $\varepsilon_{i,t+1}$ are truncated standard normal shocks which are uncorrelated with the aggregate shock $\eta_{t+1}$.[3] The assumption that $\varepsilon_{i,t+1}$ is firm specific requires that

$$\mathbb{E}[\varepsilon_{i,t}\varepsilon_{j,t}] = 0, \text{ for } i \neq j$$

Firm are allowed to scale operations by choosing the level of productive capacity $K_{i,t}$. This can be accomplished through investment, $I_{i,t}$, which is linked to productive capacity by the standard capital accumulation equation

$$K_{i,t+1} = (1 - \delta)K_{i,t} + I_{i,t} \tag{7}$$

[3] To ensure the existence of a solution to the firm's problem the shocks must be finite. We accomplish this by imposing (very large) bounds on the values of $\varepsilon$.

where $\delta > 0$ denotes the depreciation rate of capital. To have a model of real option, we assume investment is irreversible

$$I_{i,t} \geq 0 \tag{8}$$

### 2.3 Financing

Corporate investment as well as any distributions can be financed with either internal funds generated by operating profits or net new issues which can take the form of new debt (net of repayments) or new equity. We assume that debt, $B_{i,t}$, takes the form of a one period bond that pays a coupon $c_{i,t}$. Thus we allow the firm to refinance the entire value of its outstanding liabilities in every period. Formally, letting $B_{i,t}$ denote the book value of outstanding liabilities for firm $i$ at the beginning of period $t$ we define total debt liabilities as

$$L_{i,t} = (1 + (1 - \tau)c_{i,t})B_{i,t} \tag{9}$$

Note that both debt and coupon payments will exhibit potentially significant time variation and will depend on a number of firm and aggregate variables.

When firms change the amount of debt outstanding, they incur a cost. We define debt issuance costs in terms of changes in total liabilities, $L_{i,t+1} - L_{i,t}$. Firms face fixed and proportional debt issuance costs denoted by $\phi_0$ and $\phi_1$ respectively.[4] Formally, debt issuance costs are given by

$$\Phi(L_{i,t}, L_{i,t+1}) = \phi_{0,t}\mathbb{I}_{\{L_{i,t+1} \neq L_{i,t}\}} + \phi_1|L_{i,t+1} - L_{i,t}| \tag{10}$$

Firms can also raise external finance by means of seasoned equity offerings. Following the existing literature, we consider fixed and proportional costs which we denote by $\lambda_0$ and $\lambda_1$ respectively.[5] Formally, letting $E_{i,t}$ denote the net payout to equity holders, total issuance costs are given by the function

$$\Lambda(E_{i,t}) = (\lambda_{0,t} + \lambda_1|E_{i,t}|)\mathbb{I}_{\{E_{i,t}<0\}} \tag{11}$$

where the indicator function $\mathbb{I}_{\{E_{i,t}<0\}}$ implies that these costs apply only in the region where the firm is raising new equity finance when net payout, $E_{i,t}$, is negative.

[4] Since productivity has a time trend, the fixed component is growing over time too. The same is true for the fixed equity issuance costs.

[5] See Gomes (2001) and Hennessy and Whited (2007).

Investment, equity payout, and financing decisions must meet the following identity between uses and sources of funds

$$E_{i,t} = \Pi_{i,t} + \tau\delta K_{i,t} - I_{i,t} + B_{i,t+1} - L_{i,t} - \Phi(L_{i,t}, L_{i,t+1}) \tag{12}$$

where again $E_{i,t}$ denotes the equity payout. Note that the resource constraint (12) recognizes the tax shielding effects of both depreciated capital and interest expenditures. Distributions to shareholders, denoted by $D_{i,t}$, are then given as equity payout net of issuance costs

$$D_{i,t} = E_{i,t} - \Lambda(E_{i,t}) \tag{13}$$

## 2.4 Valuation

The equity value of the firm, $V_{i,t}$, is defined as the discounted sum of all future equity distributions. We assume that equity holders will choose to close the firm and default on their debt repayments if the prospects for the firm are sufficiently bad, i.e., whenever $V_{i,t}$ reaches zero. The complexity of the problem is reflected in the dimensionality of the state space necessary to construct the equity value of the firm. This includes both aggregate and idiosyncratic components of demand, productive capacity, and total debt liabilities, i.e., $V_{i,t} = V(K_{i,t}, L_{i,t}, X_{i,t})$

We can now characterize the problem facing equity holders, taking coupon payments as given. These payments will be determined endogenously below. Shareholders jointly choose investment (the next period capital stock) and financing (next period total debt commitments) strategies to maximize the equity value of each firm, which accordingly can then be computed as the solution to the following dynamic program

$$V_{i,t} = \max\left\{0, \max_{K_{i,t+1}, L_{i,t+1}} \{D_{i,t} + \mathbb{E}_t\left[M_{t,t+1}V_{i,t+1}\right]\}\right\} \tag{14}$$

where the expectation in the left hand side is taken by integrating over the conditional distributions of $X_{i,t+1}$. Note that the first maximum captures the possibility of default at the beginning of the current period, in which case the shareholders will get nothing.[6] Finally, aside from the budget constraint embedded in the definition of $D_{i,t}$, the firms face the irreversibility constraint (8), debt (10) and equity issuance costs (11).

[6] In practice, there can be violations of the absolute priority rule, implying that shareholders in default still recover value. Garlappi and Yan (2008) analyze the asset pricing implications of such violations.

### 2.5 Default and Bond Pricing

We now turn to the determination of the required coupon payments, taking into account the possibility of default by equity holders. Assuming debt is issued at par, the market value of new issues must satisfy the following Euler condition

$$B_{i,t+1} = (1 + c_{i,t+1})B_{i,t+1}\mathbb{E}_t\left[M_{t,t+1}(1 - \mathbb{I}_{\{V_{i,t+1}=0\}})\right] + \mathbb{E}_t\left[M_{t,t+1}W_{i,t+1}\mathbb{I}_{\{V_{i,t+1}=0)\}}\right] \quad (15)$$

where $W_{i,t+1}$ denotes the recovery on a bond in default and $\mathbb{I}_{\{V_{it+1}=0\}}$ is an indicator function that takes the value of one when the firm defaults and zero when it remains active.

We follow Hennessy and Whited (2007) and specify the deadweight losses at default to consist of a proportional component. Thus, creditors are assumed to recover a fraction of the firm's current assets and profits net of liquidation costs. Formally the default payoff is equal to

$$W_{i,t} = (1 - \xi)(\Pi_{i,t} + \tau\delta K_{i,t} + (1 - \delta)K_{i,t}) \quad (16)$$

Since the equity value $V_{i,t+1}$ is endogenous and itself a function of the firm's debt commitments this equation cannot be solved explicitly to determine the value of the coupon payments, $c_{i,t}$. However, using the definition of $L_{i,t}$, we can rewrite the bond pricing equation as

$$B_{i,t+1} = \frac{\frac{1}{1-\tau}L_{i,t+1}\mathbb{E}_t\left[M_{t,t+1}(1 - \mathbb{I}_{\{V_{i,t+1}=0\}})\right] + \mathbb{E}_t\left[M_{t,t+1}W_{i,t+1}\mathbb{I}_{\{V_{i,t+1}=0\}}\right]}{1 + \frac{\tau}{1-\tau}\mathbb{E}_t\left[M_{t+1}(1 - \mathbb{I}_{\{V_{i,t+1}=0\}})\right]} \quad (17)$$

Given this expression and the definition of $L_{i,t}$, we can easily deduce the implied coupon payment as

$$c_{i,t+1} = \frac{1}{1-\tau}\left(\frac{L_{i,t+1}}{B_{i,t+1}} - 1\right) \quad (18)$$

Note that defining $L_{i,t}$ as a state variable and constructing the bond pricing schedule $B_{i,t+1}$ according to (17) offers important computational advantages. Because equity and debt values are mutually dependent (since the default condition affects the bond pricing equation) we would normally need jointly solve for both the coupon schedule (or bond prices) and equity values. Instead our approach requires only a simple function evaluation during the value function iteration. This automatically nests the debt market equilibrium in the calculation of equity values and greatly reduces computational complexity.

## 2.6 Credit Spreads

For tractability reasons, we solve for the optimal amount of one period debt. In the calibration, we set one period equal to one quarter. In reality, however, firms issue debt with several years of maturity. To consider the pricing implications for 5 and 10 year debt, we price hypothetical long horizon debt.[7] Assume firm $i$ borrows the amount $B_{i,t}^{(n)}$ for $n$-periods. Under the assumption that debt is issued at par, the $n$-period bond price must satisfy the following Euler condition

$$B_{i,t}^{(n)} = \left(1 + c_{i,t}^{(n)}\right) B_{i,t}^{(n)} \mathbb{E}_t \left[M_{t,t+n}(1 - \mathbb{I}_{\{V_{i,t+n}=0\}})\right] + \mathbb{E}_t \left[M_{t,t+n} W_{i,t+n} \mathbb{I}_{\{V_{i,t+n}=0\}}\right] \tag{19}$$

where $c_{i,t}^{(n)}$ denotes the $n$-period coupon rate.[8] The bond pricing equation (19) can be solved for the arbitrage-free coupon rate $c_{i,t+1}^{(n)}$ which is given

$$1 + c_{i,t}^{(n)} = \frac{1 - \chi_{i,t}^{(n)}}{\mathbb{E}_t[M_{t,t+n}] \left(1 - q_{i,t}^{(n)}\right)} \tag{20}$$

where

$$q_{i,t}^{(n)} = \mathbb{E}_t \left[\frac{M_{t,t+n}}{\mathbb{E}_t[M_{t,t+n}]} \mathbb{I}_{\{V_{i,t+n}=0\}}\right] \qquad \chi_{i,t}^{(n)} = \mathbb{E}_t \left[M_{t,t+n} R_{i,t+n} \mathbb{I}_{\{V_{i,t+n}=0\}}\right]$$

where $q_{i,t}^{(n)}$ is the risk-neutral default probability, $R_{i,t+n} = W_{i,t+n}/B_{i,t}^{(n)}$ is the recovery rate in the case of default and $\chi_{i,t}^{(n)}$ its value. Since we solve the model on a grid, the coupon rate can be easily computed by iterating over the expectations operators without having to rely on Monte-Carlo simulations as in Bhamra, Kuehn, and Strebulaev (2010).

Since we price zero coupon debt, the coupon rate is also the yield on the outstanding debt. Consequently, the $n$-period credit spread is defined as $s_{i,t}^{(n)} = 1 + c_{i,t}^{(n)} - R_{f,t}^{(n)}$. To gain a better understanding of credit risk, we define the log credit spread as log yield minus the log risk-free rate which is approximately given by

$$\log s_{i,t}^{(n)} \approx q_{i,t}^{(n)} - \chi_{i,t}^{(n)} \tag{21}$$

This equation shows that credit spreads are zero if default does not occur in expectations, implying that both $q_{i,t}^{(n)}$ and $\chi_{i,t}^{(n)}$ are zero. On the other hand, the credit spreads increase in the risk-neutral default probability $q_{i,t}^{(n)}$ and decrease in the value of the recovery rate $\chi_{i,t}^{(n)}$.

[7] A similar exercise is done in Bhamra, Kuehn, and Strebulaev (2010). There the authors assume firms issue perpetual debt. Yet they also price hypothetical finite maturity debt to be able to compare the model with the data.

[8] Here we slightly abuse notation since $B_{i,t}^{(1)} = B_{i,t+1}$ and $c_{i,t}^{(1)} = c_{i,t+1}$.

The risk-neutral probability of default can be further decomposed into the actual probability of default and a risk premium

$$q_{i,t}^{(n)} = p_{i,t}^{(n)} + \mathrm{Cov}_t\left(\frac{M_{t,t+n}}{\mathbb{E}_t[M_{t,t+n}]}, \mathbb{I}_{\{V_{i,t+n}=0\}}\right) \tag{22}$$

where the actual default probability is defined as $p_{i,t}^{(n)} = \mathbb{E}_t[\mathbb{I}_{\{V_{i,t+n}=0\}}]$ and the covariance captures a risk compensation for default risk. Since defaults tend to occur in bad times when marginal utility is high, the covariance is positive. Consequently, credit spreads are high if the risk compensation and actual default probabilities are high. Similarly, the value of the recovery rate can be written as

$$\chi_{i,t}^{(n)} = \frac{\mathbb{E}_t[R_{i,t+n}\mathbb{I}_{\{V_{i,t+n}=0\}}]}{R_{f,t}^{(n)}} + \mathrm{Cov}_t\left(M_{t,t+n}, R_{i,t+n}\mathbb{I}_{\{V_{i,t+n}=0\}}\right) \tag{23}$$

The first term is the expected cash flow discounted using the risk-free rate and the second term, the covariance, is a compensation for risk. Since marginal utility is counter-cyclical in our model and recovery rates tend to be pro-cyclical, the covariance is negative. Thus, credit spreads are large if our model endogenously generates a pro-cyclical recovery rate.

# 3 Empirical Results

In this section, we present the quantitative implications of our model. Since the model does not entail a closed-form solution, we solve it numerically. In the following, we first explain our calibration and then we provide numerical results.

## 3.1 Calibration

In order to solve the model numerically, we calibrate it to quarterly frequency. Our calibration is summarized in Table 1. For the calibration of the consumption process, we follow Bansal, Kiku, and Yaron (2007). They assume that the first and second moments of consumption growth follow two separate processes. For tractability, we model the aggregate Markov chain, $s_t$, to jointly affect the drift and volatility of consumption and to consist of five states. To calibrate the Markov chain, we follow the procedure suggested by Rouwenhorst (1995). Specifically, given the estimates in Bansal, Kiku, and Yaron (2007), we assume that the Markov chain has first-order auto-correlation of 0.95. The states for the drift, $\mu(s_t) \in \{\mu_1, ..., \mu_5\}$, are chosen such that the standard deviation of the innovation to the drift equals 0.0004 quarterly.

Similarly, the volatility states, $\sigma(s_t) \in \{\sigma_1, ..., \sigma_5\}$, are chosen to have a quarterly mean of 0.0094 and conditional standard deviation of 0.00001 quarterly.

Regarding the preference parameters of the representative agent, we assume relative risk aversion ($\gamma$) of 10, an elasticity of intertemporal substitution ($\psi$) of 2 and rate of time preference ($\beta$) of 0.995 which are common values in the asset pricing literature to generate a realistic market price of risk.

At the firm level, we set the capital share of production equal to 0.65 in line with the evidence in Cooper and Ejarque (2003). Capital depreciates at 3% quarterly rate as in Cooley and Prescott (1995). Firms face proportional costs of production of 2% similar to Gomes (2001). Since there are no direct estimates of the conditional first and second moments of the technology shock, we follow Bansal, Kiku, and Yaron (2007) and scale the drift by 2.3 and the volatility by 6.6 relative to the respective moments of the consumption process.

Firms can issue debt and equity. We set proportional equity issuance costs at 2% which is consistent with Gomes (2001) and Hennessy and Whited (2007). Altinkilic and Hansen (2000) estimate bond issuance costs to be around 1.3%. We thus assume proportional debt issuance costs of 2%. Andrade and Kaplan (1998) report default costs of about 10%-25% of asset value and Hennessy and Whited (2007) estimate default losses to be around 10%. In line with the empirical evidence, we set bankruptcy costs at 20%. The corporate tax rate $\tau$ is 15% as in Bhamra, Kuehn, and Strebulaev (2010).

Most of the following quantitative results are based on simulations. Instead of repeating the simulation procedure, we summarize it here. We simulate 1,000 economies for 100 years each consisting of 3,000 firms. We delete the first 20 years of simulated data as burn in period. Defaulting firms are replaced with new born firms, which start at the steady state level capital and debt, such that the mass of firms is constant over time.

### 3.2 Pricing

Before we report quantitative implications for financing policies, we are interested whether our specification for the consumption process and the pricing of the market return and risk-free asset are in line with the data. To this end, we report unconditional moments generated by the consumption and equity value process in Table 2. This table shows cross simulation averages where $\mathbb{E}[\Delta c]$ denotes mean consumption growth, $\sigma(\Delta c)$ consumption growth volatility, $AC_1(\Delta c)$ the first-order autocorrelation of consumption growth, $\mathbb{E}[r_f]$ mean risk-free rate, $\sigma(r_f)$ risk-free rate volatility, $\mathbb{E}[r_m]$ average market rate, and $\sigma(r_m)$ stock market volatility. All moments are annualized. The data is taken from Bansal, Kiku, and Yaron (2007).

Our calibration for the Markov model (2) for consumption is largely consistent with the data. The unconditional mean and volatility of consumption growth match the data well but realized consumption is not sufficiently persistent. Since the asset pricing implications of recursive preferences are mainly driven by the persistence of the Markov process, this feature of the Markov process lowers the market price of risk and explains why the aggregate market return is lower in the model than in the data. However, the calibration almost matches the empirical Sharpe ratio. Moreover, given countercyclical volatility in consumption growth, the market price of risk is time-varying and countercyclical. The average unconditional risk-free rate generated by the model is similar in the data but it is not volatile enough. In the model, the risk-free rate changes with the state of the Markov chain and its persistence causes a very stable risk-free rate over time.

### 3.3 Corporate Policies

We now illustrate the model's quantitative implications for optimal firm behavior. In Table 3, we report unconditional moments of optimal corporate policies generated by the model. This table shows cross simulation averages of the average annual investment to asset ratio and its volatility, the frequency of equity issuances, average new equity to asset ratio, average book to market ratio and its volatility, book leverage and market leverage. The data are from Hennessy and Whited (2007), Davydenko and Strebulaev (2007) and Covas and Den Haan (2011).

Table 3 illustrates that the corporate financing and investment policies are generally consistent with the data. Based on the calibrated parameter values for depreciation and capital adjustment costs, the model is able to match the average investment to asset ratio and its volatility. The magnitude of the equity issuance costs parameter renders a realistic frequency of equity issuances but the magnitude of equity issuance to assets in place is slightly too large. The average book to market ratio is related to the curvature in production function as well as the investment and default option. Without the default option, the market to book ratio would be lower and closer to the data.

The most important statistics of this table are book and market leverage. Since one goal of this paper is to generate a realistic credit spread, it is crucial that the model implied leverage ratios are compatible with empirical estimates. This is important since credit spreads are increasing in default risk coming from leverage. Book leverage is defined as the ratio of the value of outstanding debt relative to the sum of debt and the book value of capital, i.e. $B/(B+K)$ and market leverage uses a similar definition but replaces the book value of capital with its market value, i.e., $B/(B+V)$. Even though book leverage is larger in the model than in the data, average market leverage is close to empirical estimates for BBB rated firms.

In Table 4, we illustrate firms' cyclical behavior by means of simple correlations of firm characteristics with GDP growth. While in our one-factor economy the correlations are, not surprisingly, a little high, the model broadly qualitatively matches firms' cyclical behavior rather well. In line with the data, investment is strongly procyclical. Investment expenditures raise firms' needs for external financing, which, given the tax advantage on debt, will come through a mix of equity and debt issuance. This makes both equity and book leverage procyclical as well. While firms will also issue equity and additional debt in order to cover financing shortfalls in downturns, investment opportunities are sufficiently procyclical to be the dominating effect. On the other hand, market leverage, again in line with the empirical evidence, is countercyclical in the model. This is because our model almost matches the volatility of stock returns in the data, as it accounts for time variation in risk premia.

#### 3.3.1 The Cross-Section of Leverage

We now examine the model's implications for the cross-sectional distribution of leverage across firms. To this end, we look at the popular regressions used in the empirical capital structure literature relating corporate leverage to several financial indicators (e.g., Rajan and Zingales (1995)). Specifically, we estimate the following regression equation in our simulated data set:

$$Lev_{it} = \alpha_0 + \alpha_1 \log(size_{it}) + \alpha_2 Q_{it} + \alpha_3 \frac{\Pi_{it}}{K_{it}},$$

Table 5 summarizes our findings, which are directly comparable to those in Rajan and Zingales (1995) and other similar studies. The table confirms the positive relation between firm size and leverage. An increase in firm size leads to higher levels of corporate leverage. This positive relation between leverage and firm size is coming from the concavity of the production function. The decreasing returns to scale assumption implies that large firms have more stable cash flows than small firms. Hence, as firms grow they optimally increase leverage over time. Table 5 also shows that our model is able to reproduce the observed negative relationships between leverage and either profitability or Q. Since small firms with volatile cash flows are also highly profitable and growth firms (high Q), the model generates the empirical observed relationships.

### 3.4 The Term Structure of Credit Spreads

We now turn to the pricing of corporate bonds in the model. We start by examining the term structure of credit spreads, and then turn the cross-sectional implications in the next section.

It is well known that the standard corporate bond models of default, such as Merton (1974) or Leland (1994), fail to explain observed credit spreads given historical default probabilities. This fact has been first established in Huang and Huang (2003) and is called the credit spread puzzle. The puzzle is that fairly safe BBB rated firms barely default over a finite time horizon but at the same time these bonds pay a large compensation for holding default risk in terms of a credit spread. For instance, the historical default rate of BBB rated firms is around 2% over a 5 year horizon but the yield of BBB firms relative to AAA rated firms is around 100 basis points. We summarize the empirical evidence in Table 6.

A common approach in the corporate bond pricing literature is to study the corporate policy of an individual firm at the initial date when the firm issues debt. The reason for this approach is that in the standard Leland (1994) model firms issue debt only once and thus in the long run leverage vanishes. In contrast, in our framework firms can rebalance their outstanding debt every period. Similar to Bhamra, Kuehn, and Strebulaev (2010), we study credit spreads in the cross section of firms.

To gauge whether our model generates a realistic credit spread, we simulate panels of firms as explained above. In Table 7, we report average equally-weighted credit spreads and actual default probabilities for 5 and 10 year debt. For 5 year debt, our model generates a credit spread of 105 basis points relative to 103 basis points in the data. For 10 year debt, the model implied credit spread is close to 120 basis points relative to 130 basis points in the data. At the same time, actual default probabilities are small. Over a five year horizon, on average 1.49% of firms default and over a 10 year horizon 3.75% of firms. Importantly, the model implied default rates are smaller than in the data.

Consequently, our investment based model can generate realistic credit spreads jointly with default probabilities and market leverage. Three mechanisms drive this result. First, our model generates investment, financing and most importantly, default policies of firms that are consistent with the empirical evidence. As we will explore below, this requires a careful modeling of the costs of investing, as well as of financial transaction costs, such as equity issuance and debt issuance costs. Second, cross-sectional heterogeneity in asset composition and leverage raise the average credit spread because the value of both the investment and default option are convex functions of the state variables. Third, as default rates are strongly countercyclical, investors require risk premia on defaultable bonds. Our model with time-varying macroeconomic risk and recursive preferences generates risk premia and a countercyclical market price of risk in line with the data, allowing the model to match the term structure of credit spreads. In the Section 3.6, we analyze the sensitivity of these results to our modeling assumptions.

To gain a better understanding of the mechanism driving credit spreads, we use the decomposition provided in Equation (21). Figure 2 displays actual default probabilities, $p_{i,t}^{(n)}$, as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for $\tau = 5$ year maturity debt and the two bottom graphs for $\tau = 10$ year maturity debt. For the solid blue line the aggregate Markov chain is one standard deviation below its mean and for the dashed red line one standard deviation above it. Similarly, Figure 3 displays risk-neutral default probabilities, $q_{i,t}^{(n)}$, Figure 4 the value of the recovery rate in the cause of default, $\chi_{i,t}^{(n)}$, and Figure 5 credit spreads, $s_{i,t}^{(n)}$.

Figures 2 and 3 illustrate that higher capital levels lower default probabilities by increasing collateral. On the other hand, more debt liabilities raise default probabilities, which is consistent with intuition. Moreover, default probabilities are higher in recessions (blue line) than in booms (red line) when the drift in productivity is lower and idiosyncratic shocks are more volatile. Default probabilities also increase over in time booms but decrease over time in recessions. Figure 5 illustrates that credit spreads fall with capital but rises with debt. Moreover, credit spreads are counter-cyclical and increase over time in booms and recessions. Two mechanisms drive this result: First, as discussed, default probabilities are countercyclical, and second, the market price of risk is countercyclical. This is inherent in our specification of the consumption growth process, namely, volatilities of consumption growth are higher in downturns, in line with the empirical evidence in Bansal, Kiku, and Yaron (2007).

### 3.5 The Cross-Section of Credit Spreads and Default Risk

While Tables 7 shows that our model is quantitatively consistent with the level and the dynamics of the term structure of credit spreads, our model also has implications for the cross-sectional determinants of spreads, and similarly, for the cross-sectional determinants of default probabilities. Tables 8 and 9 summarize these results. These results are related to a large empirical literature on the determinants of credit spreads and on default prediction and highlight the role of investment and endogenous asset composition in a model of corporate bond pricing. We adopt the empirical approach of this line of work by running regressions of credit spreads and default probabilities on a set of explanatory variables in our simulations. Specifically, beyond leverage, we use proxies for investment opportunities such as market-to-book and investment-to-asset ratios as explanatory variables[9], as well as size and profitability.

Table 8 reports regression results for credit spreads. The relevant credit spread is the spread on 5 year corporate bond. Panel A reports results for our benchmark specification. The first univariate regression of credit spreads on market leverage confirms that in the model, as expected and in line with the empirical evidence, leverage is an important and significant determinant of credit spreads. On the other hand, the following regressions suggest that variables capturing firms' investment opportunities and behavior carry additional explanatory power for spreads beyond leverage. In particular, including market-to-book and the investment-to-asset ratio in the regressions, results in significant point estimates, and, perhaps more importantly, increased explanatory power of the regressors as measured by the $R^2$. This finding is robust to including further variables used in standard capital structure regressions, namely size and profitability. These variables are significant as well, and not surprisingly, appear with negative coefficients, even controlling for leverage. This suggests that credit spreads are related to corporations' investment decisions in a robust way.

On the other hand, the fact that investment proxies enter with a positive sign is more noteworthy. Broadly, and even controlling for leverage, firms with higher investment opportunities have higher spreads. Intuitively, firms with a high market-to-book ratio derive a large fraction of their value from growth options. Our results indicate that asset composition

[9]We also included asset growth and indicators for distributions as proxies for investment opportunities in the regressions, with qualitatively similar results.

therefore matters for corporate bond prices. One way of interpreting this result is to note a growth option effectively represents represents a levered claim on an asset in place, and hence is riskier. In our model, this is reflected in the concavity of the production function. On average, smaller firms with higher growth opportunities will thus have more volatile cash flows than large firms. Accordingly, firms with high market-to-book correspond to firms with more growth options and are thus riskier than firms which consist mostly of assets in place, and this reflected in their credit spreads. On average thus, for the same amount of debt, growth firms have higher default rates than value firms, and hence higher spreads.

To the extent that credit spreads reflect firms' asset composition, one would expect that this link is inherently tied to aggregate macroeconomic conditions. Indeed, aggregate investment is strongly procyclical, as is market-to-book and related measures of investment opportunities, while market leverage is countercyclical. Table 4 documents that our model is consistent with this evidence. Therefore the value and moneyness of growth options is procyclical, while the value of moneyness of default options is countercyclical. It is therefore natural to assume that the determinants of credit spreads are inherently conditional on macroeconomic conditions. Panels B and C investigate this hypothesis in the context of our model.

Panel B reports regressions in samples that contained exclusively prolonged expansions, while panel C reports the corresponding results for samples containing extended recessions. When economies grow steadily over extended periods of time, investment opportunities abound. This boosts market-to-book, reflecting growth options getting into the money, which is followed by high investment rates. Increasingly volatile cash flows then lead to higher default probabilities in the future which drive up credit spreads. One would therefore expect the positive link between proxies for investment opportunities and credit spreads to be particularly pronounced in booms. This intuition is confirmed in panel B which leads to a strong quantitative prediction of our model. Proxies for investment opportunities are considerably stronger determinants of credit spreads in long booms than across the cycle. Thus, in good times, growth options come into the money, increasing implicit leverage of the option and hence increasing the beta of the firm. Similarly, upon exercise of the growth option, financial leverage increases due to partial debt financing. This makes the firm riskier, increasing credit spreads.

Interestingly, while still positive and significant, the coefficient on leverage in a regressions is fairly small, implying that the correlation between leverage and credit spreads is fairly weak. This reflects the inherent endogeneity of growth options and leverage in the model. As reported in 5 the model, in line with the empirical evidence, generates a negative link between growth opportunities as measured by market-to-book and leverage, so that growth firms have low leverage on average. This is particularly so during expansions, when growth firms are risky and therefore endogenously choose low leverage. The small coefficient above therefore has a natural interpretation: Asset risk and leverage risk are inversely related in our model, so that the unconditional link is weak. Unconditional regressions without controlling for the risk of assets are therefore unlikely to be very informative. Additionally, the negative link between size and spreads is more pronounced in booms, reflecting higher riskiness of smaller firms, and between profitability and spreads less so, reflecting less sensitivity of spreads to external financing.

These effects are reversed in samples containing long recessions. In such samples, proxies for investment opportunities predict credit spreads negatively, conditional on leverage. This effect derives from the interplay between investment and default options. In bad times, assets in place that come with high leverage rather than growth options are risky, reflecting operating leverage. This makes it more likely for firms which derive most of their value from assets in place to default in bad times. On the other hand, the default option makes defaulting in bad times more valuable. Quantitatively, these effects are exacerbated due our assumption of irreversible investment[10]. The negative link between profitability and spreads is now more pronounced, as an additional dollar of internal funds is worth more in bad times. This is in contrast to the link between size and spreads, which is less pronounced, reflecting fewer investment opportunities for smaller growth firms, and hence more stable cash flows.

Overall therefore the effect of investment options on credit spreads is thus conditional on macroeconomic conditions, positive in good times, and negative in bad times. Unconditionally, in our calibration, the positive effect of investment proxies on spreads dominates. These results can be understood through the endogenous interaction of asset risk and leverage risk, given macroeconomic conditions. In good times, growth options come in the money, rendering the cash flows of growth firms volatile, and more correlated with aggregate growth and hence

[10]We also solved versions of the model with disinvestment options. Qualitatively, the significance of the results prevails, as long as there disinvestment is costlier then investment.

risky. Optimally, such firms choose lower leverage. On the other hand, large firms have fairly stable cash flows, and therefore choose higher leverage. The resulting effect on spreads is hence weak. In downturns, growth firms do not invest much and have low leverage, and hence fairly stable cash flows, exhibiting low risk. On the other hand, large firms would like to disinvest, but are prevented from doing so, and moreover, have high leverage, and cannot sell assets to delever. This makes the latter firms very risky, which will be reflected in high spreads. More broadly, a similar intuition applies to stock returns, and would suggest that part of the value premium is driven by financial leverage.

Given that credit spreads reflect default probabilities, the previous results suggest that investment proxies should be useful in predicting default rates. We confirm this intuition in Table 9, where we report logit regressions of default probabilities on a set of explanatory variables. This relates to a long empirical literature on default prediction. Consistent with the results on credit spread determinants, our model also predicts that proxies for investment opportunities are significant determinants of default probabilities, even when controlling for leverage. The intuition from above directly applies: Investment opportunities signal future financing needs, which will be reflected in future default probabilities. Since investment opportunities depend on macroeconomic conditions, this link will equally be conditional on these states. In particular, in good times firms deriving a large fraction of their value from growth opportunities will be particularly exposed to aggregate risk, exacerbating the effect of growth options on risk. Similarly, the reverse effect holds in bad times.

### 3.6 Sensitivity Analysis

So far, we have documented that our model generates a term structure of credit spreads in line with the empirical evidence, and have provided an analysis of the cross-section of credit spreads in our investment-based setup. While, as demonstrated by several authors (Hackbarth, Miao, and Morellec (2006), Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Chen (2010)), substantial credit risk premia as compensation for macroeconomic conditions go a long way towards explaining this "credit spread puzzle" in endowment economics, production economies place considerably tighter restrictions on this link, as we now explore. In particular, our results suggest that our cross-sectional implications and the term structure of credit spreads are closely linked.

#### 3.6.1 Term Structure

Table 7 provides some sensitivity analysis concerning the model implied term structure of credit spreads. More specifically, it reports the term structure of default probabilities and credit spreads in our benchmark model (model I) along with three related specifications. Model II removes any financial transactions costs by setting $\lambda_0$, $\lambda_1$, $\phi_0$ and $\phi_1$ to zero. In other words, issuing equity and debt are costless. On the other hand, model III removes the investment irreversibility constraint, that is, making investment completely reversible, but retains financial transaction costs. Model IV, finally, removes both investment irreversibility and transaction costs.

Table 7 shows that the results on credit spreads and default probabilities are quite sensitive to the underlying model of investment and financing. Removing financial transactions costs, although small in magnitude, reduces the 5 year spread by 35 basis points. Qualitatively, this result is intuitive: removing equity issuance costs makes it cheaper for firms to roll over exiting debt by issuing new equity and removing debt adjustment costs makes it cheaper to delever. One can show, that fixed costs associated with financial transactions are crucial for this result. However, the magnitudes involved suggest that a careful modeling of financial costs is essential. Second, investment adjustment costs matter as well. Model III shows that removing any obstructions to downward adjustment of the capital stock decrease the 5 year spread by 45 basis points. Qualitatively, this result appears intuitive again. When investment is reversible firms can delever very effectively by selling off their capita stock, which will naturally reduce default risk. Finally, model IV shows that removing both disinvestment and financing obstructions reduce the spread by another 10 basis points. Quantitatively, these result suggest that disinvestment obstructions have stronger effects on spreads than refinancing obstructions.

Intuitively, one would guess that removing any disinvestment and refinancing obstructions would drive credit spreads essentially down to zero. However, removing such obstructions affects corporate policies in two ways, both reflected in spreads, and that work in opposite directions. First, anticipating that they will be able to delever quickly, firms will lever up more in expansions, driving up average leverage ratios, and hence, all else equal, default probabilities and credit spreads. Indeed, as reported in the table, leverage ratios are increasing through model specifications. On the other hand, this makes leverage more volatile, and debt issuance more procyclical. This in turn reduces the countercyclicality of market leverage and default probabilities. Such effect will work to reduce credit spreads through the risk premium channel: default rates become less correlated with consumption growth and the risk premium falls.

In sum, these results suggest that in a production economy two ingredients are necessary to rationalize the empirical term structure of credit spreads, namely both financial and real frictions. Financial frictions involve equity and debt issuance and adjustment costs, and real frictions involve frictions to the downward adjustment of the capital stock. We will now present evidence that these frictions are also important to generate the cross-sectional patterns in credit spreads documented above.

### 3.6.2 Cross Section

In Table 10 we report cross-sectional credit spread regressions as documented above, but now in models I, II, III and IV. While leverage unconditionally enters positively and significantly, the interesting result is that in model II the coefficient on book-to-market becomes borderline insignificant, while in models III and IV it is indistinguishable from zero. Similarly, the explanatory power of leverage is increasing through models, while the additional explanatory power of book-to-market vanishes. In other words, in a model without financial transaction costs and real frictions, leverage becomes a sufficient statistic for credit spreads and proxies for investment opportunities do not add any explanatory power. The intuition for this result is quite simple. In the absence of frictions, firms will endogenously adjust leverage just to the point that asset risk is maximally offset by leverage risk. In other words, a firm with high asset risk will 'target' a leverage ratio so low that the asset composition will no longer affect credit spreads. Hence, such a 'target leverage ratio' subsumes all the information about credit spreads contained in asset composition, or vice versa, asset composition will subsume all the information that is in leverage. As Table 10 documents, this changes in the presence of frictions. Frictions prevent firms from adjusting to target leverage, so that asset risk and leverage risk are not completely aligned, and either of them will carry predictive power for overall firm risk, and hence credit spreads. As the table indicates, the predictive power is increasing in the degree of frictions, or alternatively, in the degree of deviations from target leverage. As our earlier discussion suggests, in a production economy, matching the term structure of credit spreads dictates the magnitude of these frictions, and hence puts restrictions on the cross-section of spreads as well.

These results suggest that deviations from target leverage are reflected in credit spreads. Several authors have pointed out the importance of financial adjustment costs for capital structure dynamics (Leary and Roberts (2005), Strebulaev (2007)). We exploit the information in credit spreads to calibrate the magnitude of these costs. Moreover, our results suggest that in order to match credit spreads the magnitude of real adjustment costs needs to be sharply countercyclical. This in turn implies that deviations from target leverage should be particularly pronounced in downturns. In other words, we would expect that adjustment to target leverage should be slower in recessions than in expansions. We quantify this intuition by means of target adjustment regression, following Flannery and Rangan (2006). More specifically, we estimate

$$\text{Lev}_{i,t+1} = (\lambda\beta)X_{i,t} + (1-\lambda)\text{Lev}_{i,t} + \epsilon_{t+1}$$

where $\lambda$ reflects the speed of adjustment to target leverage. Following Flannery and Rangan (2006) we parameterize target leverage as a function of a number of firm characteristics, summarized in a vector $X_{i,t}$. In our case, we include Tobin's Q, size and profitability. The results are reported in table 11. We focus on the dynamics in expansions relative to downturns. As expected, the regression yields a higher coefficient on lagged leverage in recessions, that is, a lower $\lambda$. Accordingly, in our model the speed of adjustment is lower in recessions that in expansions. This has a natural interpretation in this context, given by the asymmetry of the adjustment cost, namely infinite downward adjustment costs. However, these costs were dictated by the term structure of credit spreads, suggesting that slow adjustment to target in bad times and a high credit spreads are two sides of the same coin.

### 3.7 Aggregate Investment and Credit Spreads

A growing body of empirical work indicates that firms' real investment decisions are affected by the corporate bond market. In particular, there is now substantial evidence that credit spreads predict aggregate investment growth (Lettau and Ludvigson (2002)). Similarly, Philippon (2009) shows that a bond market based Q explains most of the variation in aggregate investments whereas an equity market based Q fails.

In this section, we aim to replicate the first finding with our model. In Table 12, we regress next quarter's aggregate investment growth, $\Delta I_{t+1}$, on the aggregate credit spread, $s_t$,

$$\Delta I_{t+1} = \alpha + \beta s_t + \epsilon_{t+1} \qquad \epsilon \sim \mathcal{N}(0, \sigma)$$

In the data, we use quarterly real private fixed investments and as a measure of the aggregate default spread we use the difference between the yield of seasoned BBB and AAA rated firms as reported by Moody's. The data is at quarterly frequency and covers the period 1955.Q1 to 2009.Q2. We run the same regression in the data and on simulated data. In the model, aggregate investment is the sum of firm level investment decisions and the aggregate credit spread is the average equally-weighted credit spread across firms with 10 year maturity.

In Figure 1 we plot both time series. The negative correlation between the credit market and investments is apparent, meaning that more costly access to debt markets causes a reduction in real investments. Specifically, the first regression of Table 12 shows that a one percent increase in the annualized credit spread leads to reduction of 1.7% in investments with an $R^2$ of 7.7%. This estimated sensitivity is both statistically and economically significant. Using simulated panels of firms, our model can reproduce the sensitivity of investments to the costs of borrowing. The second regression of Table 12 shows that aggregate investments falls by 1.5% after a one percent increase in the aggregate credit spread which is close to the empirical estimate.

A common approach in corporate finance as well as macroeconomic models is to ignore the pricing of aggregate risk. Typically, in these models quantity dynamics are largely unaffected by movements in risk premia, implying a separation of quantity and prices as in Tallarini (2000). To demonstrate that such a separation breaks down in the presence of financing frictions, we alternatively price debt when the agent is risk neutral. In this case, the expectations are not taken under the risk neutral but the actual measure and the bond pricing relation (19) simplifies to

$$B_{i,t}^{(n)} = \left(1 + \tilde{c}_{i,t}^{(n)}\right) B_{i,t}^{(n)} \beta^n \mathbb{E}_t \left[ (1 - \mathbb{I}_{\{V_{i,t+n}=0\}}) \right] + \beta^n \mathbb{E}_t \left[ W_{i,t+n} \mathbb{I}_{\{V_{i,t+n}=0\}} \right]$$

The risk neutral coupon $\tilde{c}$ only reflects actual default probabilities but no compensation for bearing default risk. The risk neutral credit spread is the difference between the risk neutral coupon and the risk-free rate with identical maturities.

The third regression of Table 12 shows that the risk neutral credit spread looses its ability to forecast future investment growth. This finding implies that it is the risk component in credit spreads which drives most of the time variation in aggregate investment growth. We thus highlight the importance of accounting for macroeconomic risks in jointly explaining corporate financing and investment decisions.

## 4 Conclusion

Recent years have seen considerable research on credit risk and corporate bond pricing. In spite of these efforts, the empirical success of the leading class of corporate bond pricing models, namely structural models of default, is rather limited. In this paper we argue and provide quantitative evidence that the empirical performance of structural models could be significantly improved by accounting for firms' investment options. While state-of-the-art structural bond pricing models take the evolution of firms' assets as exogenously given, recent empirical evidence suggests tight links between real investment and credit spreads.

Using a tractable model of firms' investment and financing decisions we show that the link between leverage and credit spreads is significantly weakened in the presence of investment options and that variables proxying for such investment options gain explanatory power for credit spreads. Furthermore, we show that the link between leverage and credit spreads is likely conditional on investment options and macroeconomic conditions and risk. Intuitively, while low-leverage growth firms are risky in expansions because of the call feature of their growth options, high-leverage value firms can reduce their risk given the put features of their disinvestment options in busts. This leads to a conditionally negative relationship between leverage and the risk premia embedded in their spreads. Accordingly, unconditional links between spreads and leverage are quite uninformative. This shows how accounting for the endogeneity of firms' assets and their relationship to aggregate risk is crucial for understanding credit spreads.

We document these patterns in a dynamic model of firm investment and financing with macroeconomic risk which is quantitatively consistent with the historical evidence on credit spreads. In particular, the model delivers a realistic term structure of credit spreads with a 118 bp spread for 10 year bonds from BBB firms, while keeping default rates realistically low. On the other hand, the model rationalizes the recent US experience of clustered defaults.

The quantitative success of the model is mostly driven by two features of our model. First, we use a flexible setup with Epstein-Zin preferences in conjunction with time varying macroeconomic risk in consumption and productivity, which generates sizeable risk premia in credit spreads. Second, we carefully model financial transactions costs and an asymmetry between firms' growth and disinvestment options at the firm level, which makes it harder to sell capital than to buy. Taken together, these features make it particularly costly to disinvest in bad times when macroeconomic risk is high, leading to countercyclical default clustering. Investors with Epstein-Zin preferences want to be compensated for bearing these risks. This allows our model to generate a high, volatile and sharply countercyclical credit spread, just as in the data.

From a quantitative perspective, we show that rationalizing the term structure of credit spreads in a production economy imposes tight restrictions on modeling. We document how to obtain a realistic term structure of credit spreads in a production economy and point to the importance of simultaneously accounting for real and financial frictions when explaining corporate policies. In the presence of these frictions, firms' leverage will deviate from target and asset composition becomes an important determinant of the cross-sections of credit spreads and default risk.

Our results thus suggest that understanding firm-level credit spreads requires accounting for firms' investment options as well as aggregate risk factors, variables that have been largely ignored in the structural bond pricing literature. In this paper we take a step towards an integrated framework linking firms' investment and financing decisions, macroeconomic conditions and risk to the pricing of corporate bonds.

# Appendix

## A Stationary Problem

To save on notation, we drop the index $i$ and ignore the default option in the following. Because of the homogeneity of the value function and the linearity of the constraints, we can rescale the value function by $X_t$

$$
\begin{aligned}
V(K_t, L_t, X_t) &= D_t + \mathbb{E}_t[M_{t,t+1} V(K_{t+1}, L_{t+1}, X_{t+1})] \\
V\left(\frac{K_t}{X_t}, \frac{L_t}{X_t}, 1\right) &= \frac{D_t}{X_t} + \mathbb{E}_t\left[M_{t,t+1}\frac{X_{t+1}}{X_t} V\left(\frac{K_{t+1}}{X_{t+1}}, \frac{L_{t+1}}{X_{t+1}}, 1\right)\right] \\
&= d_t + \beta^\theta \mathbb{E}_t\left[e^{-\gamma(g+\mu_c(s_t)+\sigma_c(s_t)\eta_{t+1})}\left(\frac{Z(s_{t+1})+1}{Z(s_t)}\right)^{-(1-\theta)}\right. \\
&\quad \left. \times\, e^{g+\mu_x(s_t)+\sigma_x(s_t)\varepsilon_{t+1}} V\left(\frac{K_{t+1}}{X_{t+1}}, \frac{L_{t+1}}{X_{t+1}}, 1\right)\right] \\
&= d_t + \beta^\theta e^{-\gamma(g+\mu_c(s_t))+\frac{\gamma^2}{2}\sigma_c(s_t)^2} \mathbb{E}_t\left[\left(\frac{Z(s_{t+1})+1}{Z(s_t)}\right)^{-(1-\theta)}\right. \\
&\quad \left. \times\, e^{g+\mu_x(s_t)+\sigma_x(s_t)\varepsilon_{t+1}} V\left(\frac{K_{t+1}}{X_{t+1}}, \frac{L_{t+1}}{X_{t+1}}, 1\right)\right]
\end{aligned}
$$

We define the following stationary variables

$$
k_{t+1} = \frac{K_{t+1}}{X_t} \quad b_{t+1} = \frac{b_{t+1}}{X_t} \quad l_{t+1} = \frac{L_{t+1}}{X_t} \quad d_t = \frac{D_t}{X_t} \quad e_t = \frac{E_t}{X_t} \quad i_t = \frac{I_t}{X_t}
$$

The pricing kernel is given by

$$
m_{t,t+1} = \beta^\theta e^{-\gamma(g+\mu_c(s_t))+\frac{\gamma^2}{2}\sigma_c(s_t)^2}\left(\frac{Z(s_{t+1})+1}{Z(s_t)}\right)^{-(1-\theta)}
$$

and the stationary value function $v(k_t, l_t, s_t, \Delta x_t)$ solves

$$
v(k_t, l_t, s_t, \Delta x_t) = d_t + \mathbb{E}_t\left[m_{t,t+1} e^{\Delta x_{t+1}} v(k_{t+1}, l_{t+1}, s_{t+1}, \Delta x_{t+1})\right]
$$

where

$$
\Delta x_{t+1} = g + \mu_x(s_t) + \sigma_x(s_t)\varepsilon_{t+1}
$$

The stationary value function is four dimensional because the Markov state $s_t$ matters for the pricing kernel and $\Delta x_t$ for detrending dividends as shown below.

The linear constraints in the model can now be expressed in terms of stationary variables

$$\begin{aligned}
d_t &= e_t - \Lambda(e_t) \\
e_t &= \pi_t + \tau\delta e^{-\Delta x_t} k_t - i_t + b_{t+1} - e^{-\Delta x_t} l_t - \Phi(\Delta l_{t+1}) \\
\pi_t &= (1-\tau)\left[\left(e^{-\Delta x_t}\right)^{\alpha} k_t^{\alpha} - e^{-\Delta x_t} k_t f\right] \\
\Lambda(e_t) &= (\lambda_0 + \lambda_1 |e_t|)\mathbb{I}_{\{e_t<0\}} \\
\Phi(\Delta l_{t+1}) &= \phi_0 \mathbb{I}_{\{\Delta l_{t+1}\neq 0\}} + \phi_1 |\Delta l_{t+1}| \\
\Delta l_{t+1} &= l_{t+1} - e^{-\Delta x_t} l_t \\
k_{t+1} &= (1-\delta) e^{-\Delta x_t} k_t + i_t
\end{aligned}$$

The stationary total debt liabilities are

$$l_t = (1 + (1-\tau)c_t)b_t$$

implying that

$$c_{t+1} = \frac{1}{1-\tau}\left(\frac{l_{t+1}}{b_{t+1}} - 1\right)$$

We can rewrite the bond pricing equation (15) in terms of stationary variables by detrending it with $X_t$ such that

$$b_{t+1} = \frac{\mathbb{E}_t\left[m_{t,t+1}\left(\frac{1}{1-\tau} l_{t+1}\mathbb{I}_{\{v_{t+1}>0\}} + e^{\Delta x_{t+1}} r_{t+1}\mathbb{I}_{\{v_{t+1}=0\}}\right)\right]}{1 + \frac{\tau}{1-\tau}\left(\mathbb{E}_t\left[m_{t,t+1}\mathbb{I}_{\{v_{t+1}>0\}}\right]\right)}$$

where the stationary recovery value in default is

$$r_t = \frac{R_t}{X_t} = (1-\xi)\left[\pi_t + \tau\delta e^{-\Delta x_t} k_t + (1-\delta)e^{-\Delta x_t} k_t\right]$$

# B Numerical Solution

We solve the model numerically with value function iteration. We create a grid for capital and debt liabilities, each with 50 points. The choice vector for tomorrow's capital level and debt liabilities has 250 elements for each variable. We use two dimensional linear interpolation to evaluate the value function and bond pricing equation off grid points. The aggregate Markov chain has 5 states and changes in the technology shock are approximated with 10 elements.

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**Figure 1: Investment Growth and Default Risk**

This figure displays investment growth and the default spread for the US economy. We use quarterly real private fixed investments. The default spread is the difference between Moody's BBB and AAA. The data spans the period 1955.Q1-2009.Q2.

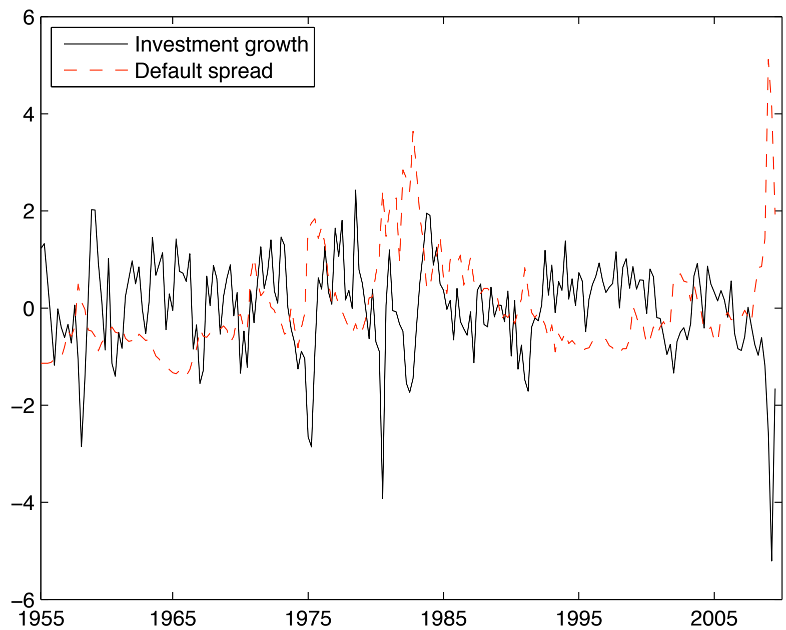

**Figure 2: Actual Default Probabilities**

This figure displays actual default probabilities as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for 5 year maturity debt and the two bottom graphs for 10 year maturity debt. For the solid blue line the aggregate Markov chain is one standard deviation below its mean and for the dashed red line one standard deviation above.

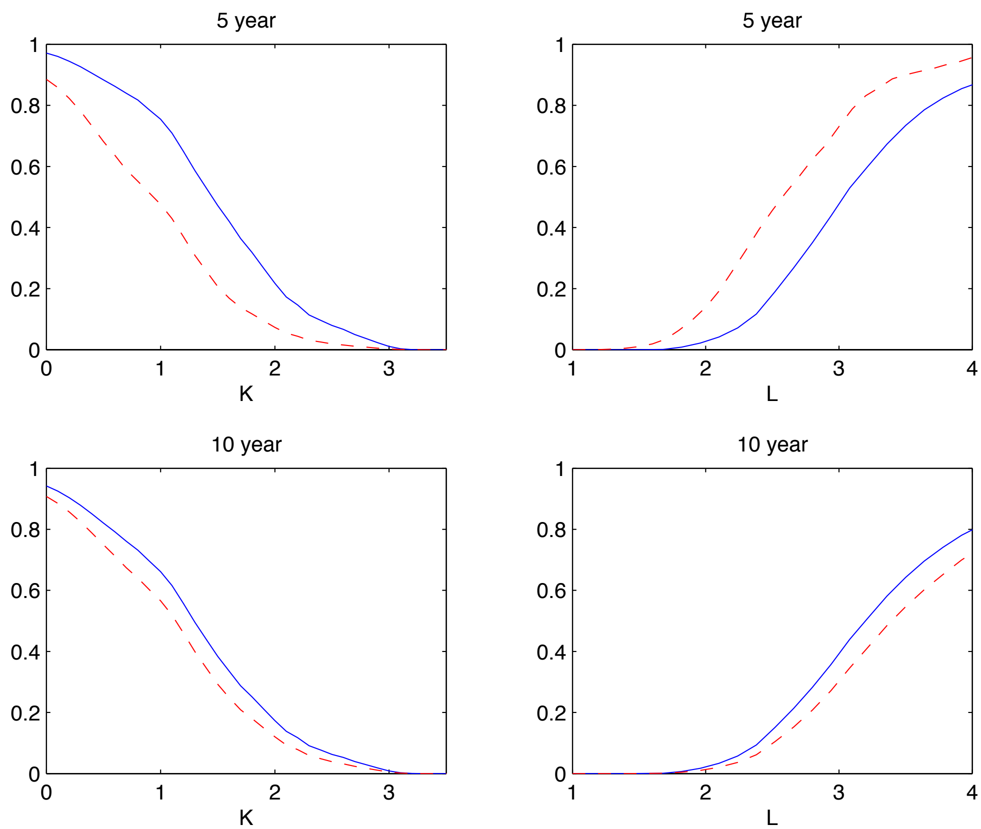

**Figure 3: Risk-Neutral Default Probabilities**

This figure displays risk-neutral default probabilities as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for 5 year maturity debt and the two bottom graphs for 10 year maturity debt. For the solid blue line the aggregate Markov chain is one standard deviation below its mean and for the dashed red line one standard deviation above.

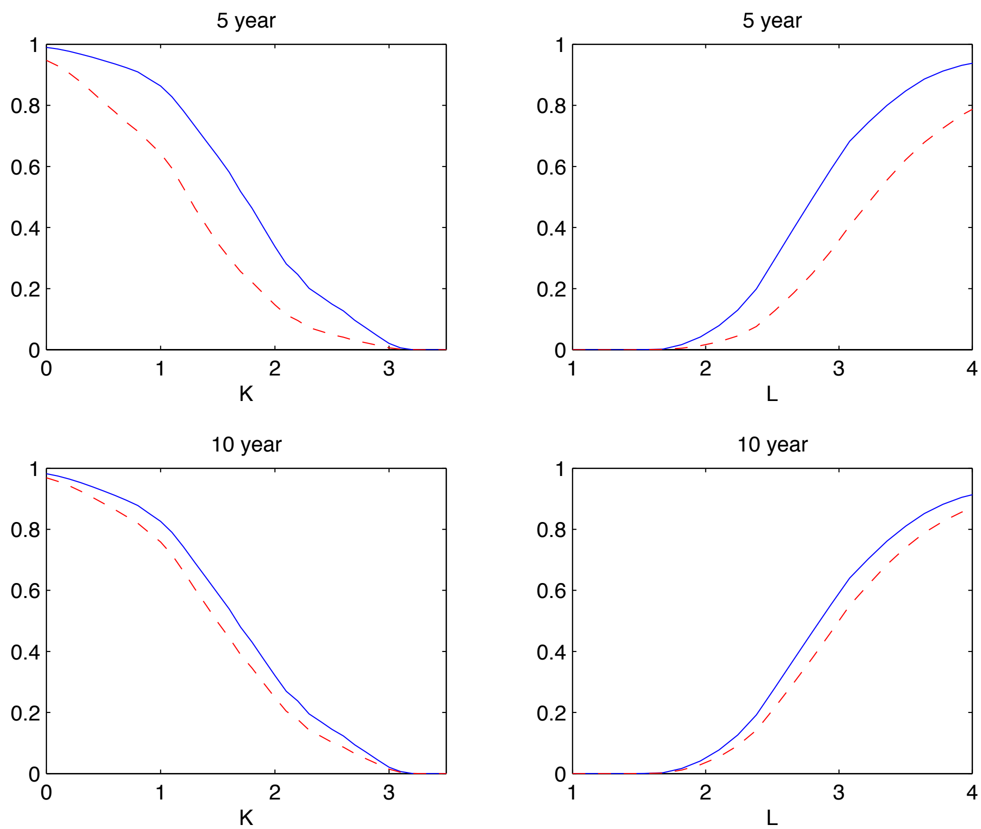

**Figure 4: Recovery Rate Value**

This figure displays the value of the recovery rate as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for 5 year maturity debt and the two bottom graphs for 10 year maturity debt. For the solid blue line the aggregate Markov chain is one standard deviation below its mean and for the dashed red line one standard deviation above.

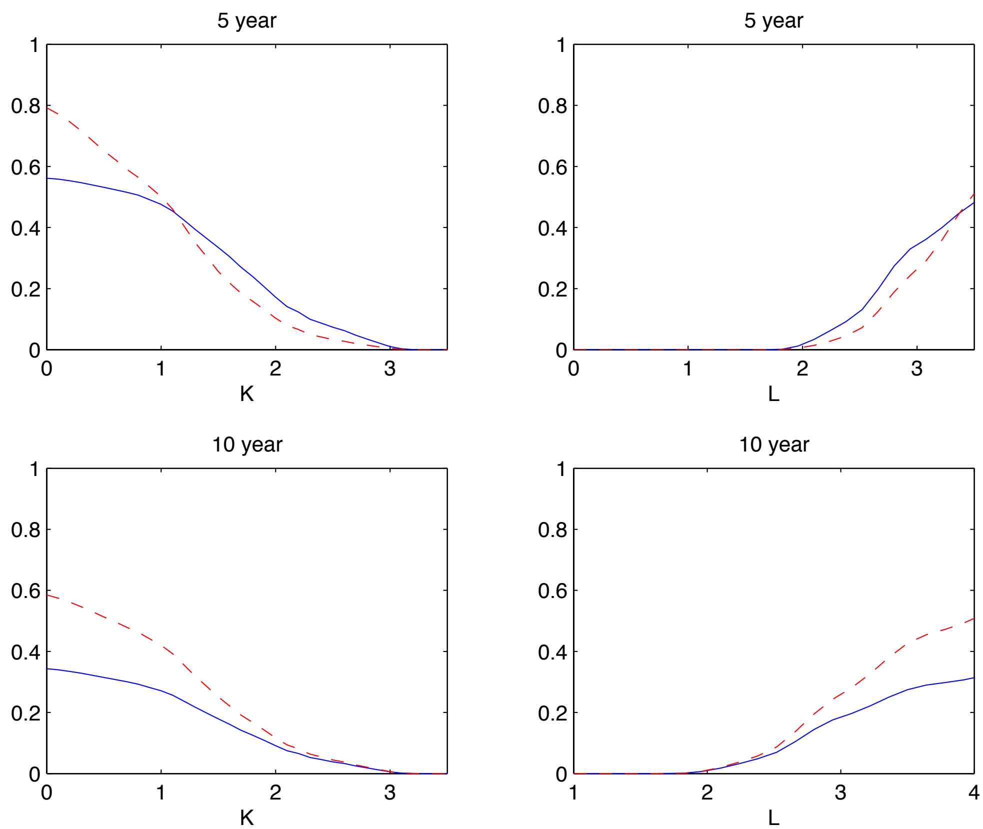

**Figure 5: Credit Spreads**

This figure displays credit spreads as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for 5 year maturity debt and the two bottom graphs for 10 year maturity debt. For the solid blue line the aggregate Markov chain is one standard deviation below its mean and for the dashed red line one standard deviation above.

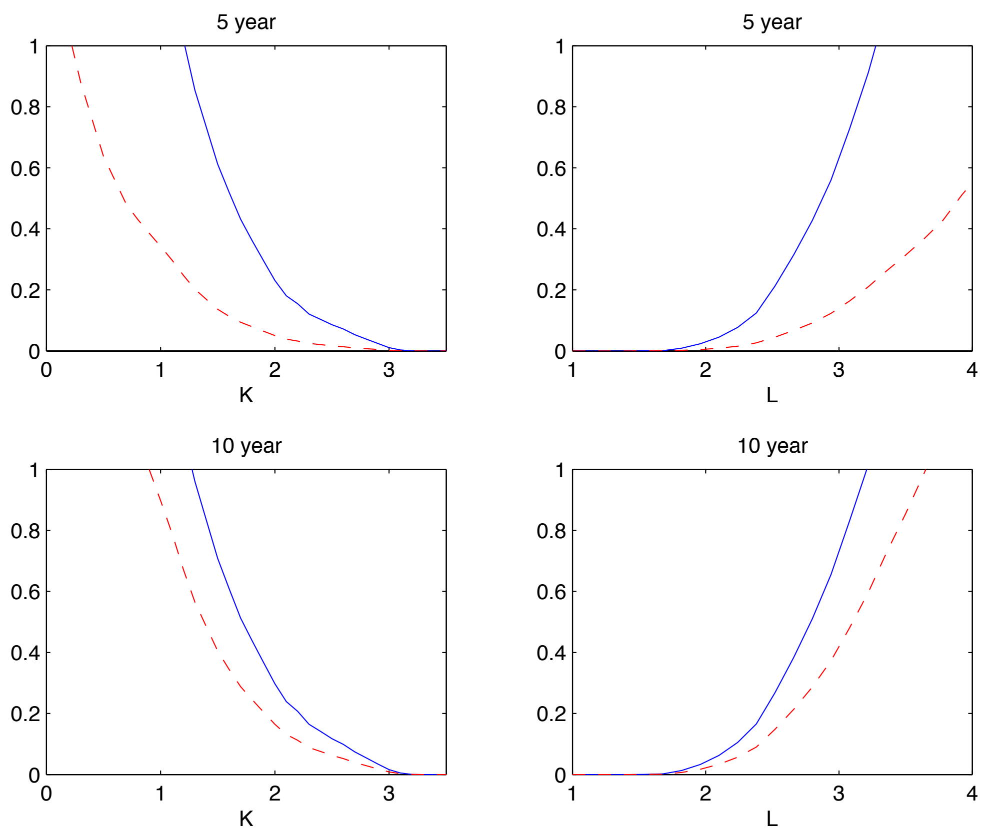

**Table 1: Calibration**

This tables summarizes our calibration used to solve and simulate our model. All values are quarterly.

| Description | Parameter | Value |
|---|---|---|
| Rate of time preference | $\beta$ | 0.995 |
| Relative risk aversion | $\gamma$ | 10 |
| Elasticity of intertemporal substitution | $\psi$ | 2 |
| Growth rate of consumption | $g$ | 0.005 |
| Persistence of Markov chain | $\rho$ | 0.95 |
| Capital share | $\alpha$ | 0.65 |
| Depreciation of capital | $\delta$ | 0.03 |
| Proportional costs of production | $f$ | 0.02 |
| Corporate tax rate | $\tau$ | 0.15 |
| Fixed equity issuance costs | $\lambda_0$ | 0.01 |
| Proportional equity issuance costs | $\lambda_1$ | 0.02 |
| Fixed debt issuance costs | $\phi_0$ | 0.01 |
| Proportional debt issuance costs | $\phi_1$ | 0.02 |
| Bankruptcy costs | $\xi$ | 0.2 |

**Table 2: Aggregate Moments**

In this table, we report unconditional moments generated by the consumption process and the firm model. We simulate 1,000 economies for 100 years each consisting of 3,000 firms. This table shows cross simulation averages where $\mathbb{E}[\Delta c]$ denotes mean consumption growth, $\sigma(\Delta c)$ consumption growth volatility, $AC_1(\Delta c)$ the first-order autocorrelation of consumption growth, $\mathbb{E}[r_f]$ mean risk-free rate, $\sigma(r_f)$ risk-free rate volatility, $\mathbb{E}[r_m]$ average market rate, and $\sigma(r_m)$ stock market volatility. All moments are annualized. The data are from Bansal, Kiku, and Yaron (2007).

| Moment | Unit | Data | Model |
|---|---|---|---|
| $\mathbb{E}[\Delta c]$ | % | 1.96 | 1.96 |
| $\sigma(\Delta c)$ | % | 2.21 | 2.08 |
| $AC_1(\Delta c)$ | | 0.44 | 0.28 |
| $\mathbb{E}[r_f]$ | % | 0.76 | 1.10 |
| $\sigma(r_f)$ | % | 1.12 | 0.52 |
| $\mathbb{E}[r_m]$ | % | 8.27 | 6.84 |
| $\sigma(r_m)$ | % | 20.10 | 17.37 |

**Table 3: Unconditional Firm-Level Moments**

In this table, we report unconditional moments generated by the model. We simulate 1,000 economies for 100 years each consisting of 3,000 firms. This table shows cross simulation averages. The data are from Hennessy and Whited (2007), Davydenko and Strebulaev (2007) and Covas and Den Haan (2011).

| Moment | Data | Model |
|---|---|---|
| Avg. annual investment to asset ratio | 0.130 | 0.093 |
| Volatility of investment to asset ration | 0.006 | 0.028 |
| Frequency of equity issuances | 0.099 | 0.127 |
| Avg. new equity to asset ratio | 0.042 | 0.133 |
| Avg. market to book ratio | 1.493 | 1.845 |
| Volatility of market to book ratio | 0.230 | 0.278 |
| Book leverage | 0.587 | 0.614 |
| Market leverage | 0.367 | 0.352 |

**Table 4: Firm Behavior over the Business Cycle**

This table reports correlation coefficients of key macro and financial variables in the model. We simulate 1,000 economies for 100 years each consisting of 3,000 firms. For flow variables we use correlations between growth rates. For leverage we report correlation with end of period ratios. Empirical sources are the Bureau of Economic Analysis and the Board of Governors of the Federal Reserve.

| Moment | Data | Model |
|---|---|---|
| Investment | 0.81 | 0.87 |
| Equity Issuance | 0.10 | 0.18 |
| Market Leverage | -0.11 | -0.69 |
| Book Leverage | 0.07 | 0.21 |
| Credit Spread | -0.33 | -0.54 |
| Default Rate | -0.36 | -0.83 |

**Table 5: Cross-Sectional Leverage Regressions**

This table reports results from Fama-Macbeth cross-sectional regressions of leverage measures on various measures of size, Tobin's Q, and profitability. The leverage measure in the upper panel is book leverage, and the lower panel reports analogous results for market leverage. Our size measures are (log) sales and (log) assets, respectively. For this exercise, we simulate 1,000 economies for 100 years each consisting of 3,000 firms. This table shows cross simulation averages.

| | Unconditional | Boom | Recession |
|---|---|---|---|
| Size | 1.47 | 1.65 | 1.33 |
| | (2.29) | (2.38) | (2.23) |
| Q | -0.95 | -1.03 | -0.82 |
| | (-2.17) | (-2.25) | (-2.22) |
| Profitability | -0.66 | -0.61 | -0.76 |
| | (-2.28)) | (-2.19) | (-2.29) |

**Table 6: Empirical Default Rates and Credit Spreads**

Panel A reports average cumulative issuer-weighted annualized default rates for BBB debt over 5, 10, and 15 year horizons for US firms as reported by Cantor, Emery, Ou, and Tennant (2008). The first row shows mean historical default rates for the period 1920–2007 and the second row for 1970–2007. Panel B reports the difference between average spreads for BBB and AAA corporate debt, sorted by maturity. Data from Duffee (1998) are for bonds with no option-like features, taken from the Fixed Income Dataset, University of Houston, for the period Jan 1973 to March 1995, where maturities from 2 to 7 years are short, 7 to 15 are medium, and 15 to 30 are long. For Huang and Huang (2003), short denotes a maturity of 4 years and medium of 10 years. The data used in David (2008) are taken from Moody's and medium denotes a maturity of 10 years. For Davydenko and Strebulaev (2007), the data are taken from the National Association of Insurance Companies; short denotes a maturity from 1 to 7 years, medium 7 to 15 years, and long 15 to 30 years.

| Panel A: Historical BBB Default Probabilities | | | | |
|---|---|---|---|---|
| Rating | Unit | Year 5 | Year 10 | Year 15 |
| 1920 – 2007 | % | 3.142 | 7.061 | 10.444 |
| 1970 – 2007 | % | 1.835 | 4.353 | 7.601 |
| **Panel B: BBB/AAA Spreads** | | | | |
| Rating | Unit | Short | Medium | Long |
| Duffee (1998) | b.p. | 75 | 70 | 105 |
| Huang and Huang (2003) | b.p. | 103 | 131 | – |
| David (2008) | b.p | – | 96 | – |
| Davydenko and Strebulaev (2007) | b.p | 77 | 72 | 82 |

**Table 7: Term Structure of Credit Spreads**

In this table, we report average 5 and 10 year credit spreads and the corresponding actual default probabilities, in different model specifications. Model I refers to the benchmark model, model II features no financial adjustment costs, model III features completely irreversible investment, and model IV features neither financial nor capital adjustment costs (reversible investment). For this exercise, we simulate 1,000 economies for 100 years each consisting of 3,000 firms. This table shows cross simulation averages.

| Moment | Unit | Data | Model I | Model II | Model III | Model IV |
|---|---|---|---|---|---|---|
| 5 year credit spread | b.p. | 103.00 | 105.13 | 71.37 | 59.25 | 49.65 |
| 5 year default probability | % | 1.83 | 1.49 | 1.06 | 0.94 | 0.83 |
| 10 year credit spread | b.p. | 130.00 | 118.62 | 85.14 | 73.51 | 58.29 |
| 10 year default probability | % | 4.35 | 3.75 | 2.81 | 2.46 | 2.17 |
| Leverage | | | 0.35 | 0.38 | 0.41 | 0.43 |

**Table 8: Cross Section of Credit Spreads**

The table reports regressions of credit spreads on a set of explanatory variables, in model simulations. The dependent variable is the 5-year credit spread. The regression results are obtained from simulations of 1,000 economies for 50 years each consisting of 3,000 firms. Panel A reports regressions from unconditional simulations, including booms and recessions as generated by our shock specification. In panel B we consider economies that are in long-lasting booms, in the sense that they are exposed to above average shock realizations. In panel C we consider economies that are in long-lasting recessions, in the sense that they are exposed to below average shock realizations. t-statistics are reported in parentheses.

| | | | | | |
|---|---|---|---|---|---|
| | | | Panel A: Unconditional | | |
| Leverage | 1.39 | 1.66 | 1.85 | 1.79 | 1.88 |
| | (2.21) | (2.13) | (2.26) | (2.33) | (2.31) |
| Market-to-Book | | 0.59 | | 0.36 | |
| | | (2.11) | | (2.15) | |
| Investment-to-Asset | | | 1.25 | | 1.12 |
| | | | (2.09) | | (2.18 ) |
| Size | | | | -1.12 | -1.08 |
| | | | | (-2.29) | (-2.34 ) |
| Profitability | | | | -0.41 | -0.27 |
| | | | | (-2.15 ) | (-2.12) |
| $R^2$ | 0.54 | 0.61 | 0.60 | 0.64 | 0.64 |
| | | | Panel B: Booms | | |
| Leverage | 0.88 | 1.42 | 1.71 | 1.88 | 1.43 |
| | (2.10) | (2.24) | (2.17) | (2.19) | (2.27) |
| Market-to-Book | | 0.73 | | 0.61 | |
| | | (2.22) | | (2.20 ) | |
| Investment-to-Asset | | | 1.38 | | 1.21 |
| | | | (2.19) | | (2.14) |
| Size | | | | -1.42 | -1.35 |
| | | | | (-2.26) | (-2.33) |
| Profitability | | | | -0.29 | -0.23 |
| | | | | (-2.08 ) | (-2.18) |
| $R^2$ | 0.53 | 0.62 | 0.61 | 0.66 | 0.65 |
| | | | Panel C: Recessions | | |
| Leverage | 1.91 | 2.02 | 2.11 | 1.96 | 2.07 |
| | (2.32) | (2.20) | (2.28) | (2.31) | (2.34) |
| Market-to-Book | | -0.19 | | -0.14 | |
| | | (-2.13) | | (-2.07 ) | |
| Investment-to-Asset | | | -0.50 | | -0.36 |
| | | | (-2.17) | | (-2.08) |
| Size | | | | -0.98 | - 0.93 |
| | | | | (-2.25) | (-2.16) |
| Profitability | | | | -0.49 | -0.43 |
| | | | | (-2.24 ) | (-2.18) |
| $R^2$ | 0.56 | 0.59 | 0.59 | 0.61 | 0.62 |

**Table 9: Cross Section of Default Risk**

The table reports logit regressions of default probabilities on a set of explanatory variables, in model simulations. The dependent variable is the 1-year default probability. The regression results are obtained from simulations of 1,000 economies for 50 years each consisting of 3,000 firms. Panel A reports regressions from unconditional simulations, including booms and recessions as generated by our shock specification. In panel B we consider economies that are in long-lasting booms, in the sense that they are exposed to above average shock realizations. In panel C we consider economies that are in long-lasting recessions, in the sense that they are exposed to below average shock realizations. t-statistics are reported in parentheses.

| | | | | | |
|---|---|---|---|---|---|
| Panel A: Unconditional | | | | | |
| Leverage | 2.13 | 2. 30 | 2.44 | 2.17 | 2.22 |
| | (2.10) | (2.21) | (2.15) | (2.27) | (2.23) |
| Market-to-Book | | 0.87 | | 0.72 | |
| | | (2.05) | | (2.11 ) | |
| Investment-to-Asset | | | 1.68 | | 1.46 |
| | | | (2.14) | | (2.09 ) |
| Size | | | | -1.51 | -1.43 |
| | | | | (-2.28)) | (-2.25) |
| Profitability | | | | -0.77 | -0.53 |
| | | | | (-2.17 ) | (-2.12) |
| $R^2$ | 0.52 | 0.60 | 0.62 | 0.63 | 0.62 |
| Panel B: Booms | | | | | |
| Leverage | 1.37 | 1.94 | 2.26 | 2.31 | 2.09 |
| | (2.24) | (2.18) | (2.31) | (2.25) | (2.17) |
| Market-to-Book | | 1.14 | | 0.92 | |
| | | (2.20) | | (2.16 ) | |
| Investment-to-Asset | | | 1.81 | | 1.58 |
| | | | (2.31) | | (2.28 ) |
| Size | | | | -1.75 | -1.63 |
| | | | | (-2.36) | (-2.32) |
| Profitability | | | | -0.56 | -0.49 |
| | | | | (-2.11) | (-2.19) |
| $R^2$ | 0.50 | 0.59 | 0.59 | 0.63 | 0.62 |
| Panel C: Recessions | | | | | |
| Leverage | 3.91 | 4.22 | 4.37 | 4.14 | 4.20 |
| | (2.42) | (2.35) | (2.40) | (2.32) | (2.36) |
| Q | | -0.44 | | -0.37 | |
| | | (-2.03) | | (-2.00 ) | |
| Investment-to-Asset | | | -0.94 | | -0.85 |
| | | | (-2.10) | | (-2.13) |
| Size | | | | -1.43 | -1.26 |
| | | | | (-2.19) | (-2.15 ) |
| Profitability | | | | -0.83 | -0.73 |
| | | | | (-2.28 ) | (-2.25) |
| $R^2$ | 0.55 | 0.57 | 0.57 | 0.59 | 0.59 |

**Table 10: Frictions and the Cross-Section of Credit Spreads**

The table reports credit spread regressions in model simulations, in different model specifications. Model I refers to the benchmark model, model II features no financial adjustment costs, model III features completely irreversible investment, and model IV features neither financial nor capital adjustment costs (reversible investment). The dependent variable is the 5-year credit spread. The regression results are obtained from simulations of 1,000 economies for 50 years each consisting of 3,000 firms. t-statistics are reported in parentheses.

| | Model I | | Model II | | Model III | | Model IV | |
|---|---|---|---|---|---|---|---|---|
| Leverage | 1.39 | 1.66 | 1.64 | 1.57 | 1.53 | 1.88 | 1.59 | 1.74 |
| | (2.21) | (2.13) | (2.24) | (2.20 ) | (2.33) | (2.26) | (2.42) | (2.31) |
| Book-to-Market | | 0.59 | | 0.63 | | 0.71 | | 0.65 |
| | | (2.11) | | (1.91) | | (1.67) | | (1.55) |
| $R^2$ | 0.54 | 0.61 | 0.56 | 0.60 | 0.60 | 0.60 | 0.62 | 0.62 |

**Table 11: Target Adjustment Regressions**

The table reports results of Fama-Macbeth target adjustment regressions of leverage on lagged leverage and explanatory variables. Following Flannery and Rangan (2005), the regressions are of the form

$$\text{Lev}_{i,t+1} = (\lambda\beta)X_{i,t} + (1-\lambda)\text{Lev}_{i,t} + \epsilon_{t+1}$$

The regression results are obtained from simulations of 1,000 economies for 100 years each consisting of 3,000 firms. Panel A reports regressions from economies that are in long-lasting booms. In panel B we consider economies that are in long-lasting recessions. t-statistics are reported in parentheses.

| Panel A: Expansion | | | |
|---|---|---|---|
| Leverage | Q | Size | Profitability |
| 0.78 | -0.08 | 0.03 | -0.13 |
| (2.33 ) | (-2.15 ) | (2.24) | (-2.18 ) |
| Panel B: Recession | | | |
| Leverage | Q | Size | Profitability |
| 0.91 | -0.04 | 0.01 | -0.06 |
| ( 2.39 ) | (-2.26 ) | (2.22) | (-2.30 ) |

**Table 12: Aggregate Investment and Credit Spreads**

In this table, we regress aggregate investment growth, $\Delta I_{t+1}$, on the aggregate credit spread, $s_t$,

$$\Delta I_{t+1} = \alpha + \beta s_t + \epsilon_{t+1} \qquad \epsilon \sim \mathcal{N}(0, \sigma)$$

In the data, we use quarterly real private fixed investments and the aggregate credit spread is the difference between Moody's BBB and AAA. The data is at quarterly frequency and covers the period 1955.Q1 to 2009.Q2. In the model, we simulate 1,000 economies for 100 years each consisting of 3,000 firms. We run the same regression in the data and on simulated data. The risk neutral credit spread is the difference between the yield of corporate debt priced under the actual probability measure and the risk-free rate. We report $t$-statistics in parentheses which are based on Newey-West standard errors with 4 lags.

| | $\alpha$ | $\beta$ | $R^2$ |
|---|---|---|---|
| Data | 0.024 | -1.674 | 0.077 |
| | (3.941) | (-2.446) | |
| Model | 0.067 | -1.486 | 0.058 |
| | (4.518) | (3.128) | |
| Risk-neutral credit spread | 0.097 | -0.184 | 0.008 |
| | (3.824) | (1.429) | |