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 financial market imperfections leverage and investment are generally correlated so that highly levered firms are also mature firms with relatively more (safe) book assets and fewer (risky) growth opportunities. 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.

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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. More specifically, while we build on the recent literature relating firms' capital structures to their investment policies (Hennessy and Whited (2005), Hennessy and Whited (2007)), 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 and disinvestment 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. 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 (?, Strebulaev

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

(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 is conditional in nature and depends on macroeconomic conditions in a model with investment options. Intuitively, as growth options pay off in good times, growth firms are riskier in expansions than value firms which derive most of their value from assets in place. Moreover, risky growth firms have low leverage in the model and the data. Conditioning on growth option and aggregate conditions thus renders the link between leverage and credit spreads negative in booms. In contrast, disinvestment options are valuable in downturns, alleviating some of the risk of highly levered firms with mostly assets in place, which renders the conditional link between leverage and credit spreads positive. 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 (2009), Chen (2008)), 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.

Our results thus suggest that understanding firm-level credit spreads requires accounting for firms' investment options as well as aggregate factors, variables that have been largely ignored in the structural bond pricing literature. The aim of this paper is therefore to provide

a step towards an integrated framework linking firms' investment and financing decisions, macroeconomic conditions and risk to the pricing of corporate bonds.

In the paper, we provide such a tractable framework that links the pricing of corporate bonds to firms' investment and financing decisions. Firms possess the option to expand as well as reduce capacity. In particular, we assume an asymmetry between firms' growth and disinvestment options, which makes it harder to sell capital than to buy it. Such investment can be financed with retained earnings, equity issuances or debt. 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 debt when the option to default is more valuable than paying back bond holders. When making these dynamics decisions, firms face costs in adjusting the capital stock as well as debt and equity issuances costs.

To price debt and equity, we introduce Epstein-Zin preferences with time varying macroeconomic risk in consumption and productivity in a cross-sectional production economy with risky corporate debt. 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. In contrast to a representative agent with power utility, an agent with Epstein-Zin preferences is not indifferent to the resolution of intertemporal macroeconomic risk. We assume that she dislikes intertemporal macroeconomic risk and it is therefore reflected in the valuation of debt and equity. This generates a sizeable compensation for countercyclical default losses in credit spreads.

Modeling macroeconomic risk explicitly is important in order to account for the price of aggregate risk in explaining the overall level of credit spreads. On the one hand, bond yields reflect expected default rates and losses. On the other hand, as corporate bonds tend to default in bad times when marginal utility is high, risk averse investors will require a risk compensation for holding these assets. Recent theoretical and empirical evidence suggests that the risk premium component accounts for most of the level and variation of corporate bond spreads (see for instance Elton, Gruber, Agrawal, and Mann (2001), Huang and Huang (2003), Almeida and Philippon (2007) and Bhamra, Kuehn, and Strebulaev (2009)).

Quantitatively, our model therefore successfully rationalizes a number empirical facts on the historical evidence on credit spreads. 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. One reason pertains to our empirical strategy, while the other is again closely linked to the availability of investment options in our model. First, we measure credit spreads in the cross section of firms as in Bhamra, Kuehn, and Strebulaev (2009). The standard approach is to measure credit spreads when firms issue new debt. In reality, however, firms adjust leverage only infrequently as shown by ?. Cross sectional heterogeneity raises the average credit spread because the value of the default option is convex in capital.

Second, and more importantly, there is an asymmetry between growth and disinvestment options, that is firms face higher costs when they sell capital than when they buy. Relative to standard structural models of default where firms' earnings streams are exogenous, in our production economy with investment options earnings are endogenous and firms could sell capital to pay off debt. As a result, firms would never default and credit spreads would be unrealistically small. Essentially, the value of the disinvestment option drives out the value of the default option.

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 (2009), Chen (2008)). 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, it adds a long run risk perspective to the literature on the

cross-section of stock returns by providing a tractable way of modelling rms' 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 rms' 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 nancial and real transaction costs.

2 Model

In this section, we rst derive the pricing kernel of the representative agent. We assume the representative agent has recursive preferences and the conditional rst 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 rm's problem. Firms choose optimal investments to maximize their equity value. Investments are nanced by retained earnings as well as equity or debt issuances. Firms can default on their outstanding debt if prospects are su ciently 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 ψ the elasticity of intertemporal substitution (EIS), and γ 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-de ned 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

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

where $\mu(s_t)$ and $\sigma(s_t)$ depend on the aggregate state of the economy denoted by s_t and η_{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 indi erent 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 rst 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 de ned 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 de ne 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 rm in a perfectly competitive environment. The ow of after tax operating pro ts, , for rm i is described by the

expression

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

where $X_{i,t}$ is a productivity shock and $K_{i,t}$ denotes the book value of the rm's assets. We use τ 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 rm 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 η_{t+1}.[2] The assumption that $\varepsilon_{i,t+1}$ is rm speci c 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

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

where $\delta > 0$ denotes the depreciation rate of capital. As in Zhang (2005), we assume that rms face convex but asymmetric adjustment costs when they decide to change their capital stock given by

$$h(I_{i,t}, K_{i,t}) = \frac{\theta_{i,t}}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t} \tag{8}$$

where the adjustment cost parameter $\theta_{i,t}$ depends on whether investments are positive or negative.

2.3 Financing

Corporate investment as well as any distributions can be nanced with either internal funds generated by operating pro ts or net new issues which can take the form of new debt (net of

[2] 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 ε.

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 the value of net new issues as

$$B_{i,t+1} - (1 + c_{i,t})B_{i,t}.$$

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 the level of outstanding debt, $B_{i,t+1} - B_{i,t}$. Since the productivity shock has a time trend, we will have to solve the stationary problem which only allows costs to be constant returns to scale. Consequently, we assume that debt issuance costs are proportional to changes in the level of outstanding debt

$$(B_{i,t}, B_{i,t+1}) = \phi|B_{i,t+1} - B_{i,t}| \tag{9}$$

Firms can also raise external finance by means of seasoned equity offerings. For added realism, we assume that these issues entail additional costs so that firms will never find it optimal to simultaneously pay dividends and issue equity. Following the existing literature, we consider proportional costs which we denote by λ.[3] Formally, letting $E_{i,t}$ denote the net payout to equity holders, total issuance costs are given by the function

$$(E_{i,t}) = \lambda E_{i,t}\mathbb{I}_{\{E_{i,t}<0\}} \tag{10}$$

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.

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

$$E_{i,t} = \quad_{i,t} + \tau\delta K_{i,t} - I_{i,t} - h(I_{i,t}, K_{i,t}) + B_{i,t+1} - (1 + (1-\tau)c_{i,t})B_{i,t} - \quad(B_{i,t}, B_{i,t+1}) \tag{11}$$

where again $E_{i,t}$ denotes the equity payout. Note that the resource constraint (11) recognizes the tax shielding effects of both depreciated capital and interest expenditures. Distributions to shareholders, denoted $D_{i,t}$ are then given as equity payout net of issuance costs

$$D_{i,t} = E_{i,t} - \quad(E_{i,t}) \tag{12}$$

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

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, defined as

$$L_{i,t} = (1 + (1 - \tau)c_{i,t})B_{i,t} \tag{13}$$

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.[4] Finally, aside from the budget constraint embedded in the definition of $D_{i,t}$, the firms face capital adjustment costs (8), debt (9) and equity issuance costs (10).

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

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

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.

[4] 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.

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

$$W_{i,t} = (1-\xi)(\;{}_{i,t} + \tau\delta K_{i,t} + (1-\delta)K_{i,t}) \tag{16}$$

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

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

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

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

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.[5] 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

[5] A similar exercise is done in Bhamra, Kuehn, and Strebulaev (2009). 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.

following Euler condition

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

where $c_{i,t}^{(n)}$ denotes the n-period coupon rate.[6] The bond pricing equation (19) can be solved for the arbitrage-free coupon rate $c_{i,t+1}^{(n)}$ which is given

$$c_{i,t}^{(n)} = \frac{1 - \mathbb{E}_t\left[M_{t,t+n} R_{i,t+n} \mathbb{I}_{\{V_{i,t+n}=0\}}\right]}{\mathbb{E}_t\left[M_{t,t+n}(1 - \mathbb{I}_{\{V_{i,t+n}=0\}})\right]} - 1 \quad (20)$$

where $R_{i,t+n} = W_{i,t+n}/B_{i,t}^{(n)}$ is the recovery rate in the case of default. 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 (2009).

Since we price zero coupon debt, the coupon rate is also the yield on the outstanding debt. Thus, the n-period credit spread is de ned as $s_{i,t}^{(n)} = 1 + c_{i,t}^{(n)} - R_{f,t}^{(n)}$. Using Equation (20) for the coupon rate, credit spreads can be expressed as

$$s_{i,t}^{(n)} = \frac{1 - \chi_{i,t}^{(n)}}{\mathbb{E}_t[M_{t,t+n}] - \xi_{i,t}^{(n)}} - \frac{1}{\mathbb{E}_t[M_{t,t+n}]} \quad (21)$$

and

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

where $\xi_{i,t}^{(n)}$ is the value of a state conditional Arrow-Debreu claim that pays one unit of consumption if the rm defaults in period $t + n$ and $\chi_{i,t}^{(n)}$ is the value of the recovery rate in default. Equation (21) shows that the credit spread is zero if default does not occur in expectations, implying that both $\xi_{i,t}^{(n)}$ and $\chi_{i,t}^{(n)}$ are zero. On the other hand, the credit spread increases in the value of the Arrow-Debreu claim of default $\xi_{i,t}^{(n)}$ and falls with the value of the recovery rate $\chi_{i,t}^{(n)}$.

To gain a better understanding of the Arrow-Debreu claim of default, we decompose it into three terms

$$\xi_{i,t}^{(n)} = \frac{\text{Cov}_t\left(\frac{M_{t,t+n}}{\mathbb{E}_t[M_{t,t+n}]}, \mathbb{I}_{\{V_{i,t+n}=0\}}\right) + \mathbb{E}_t[\mathbb{I}_{\{V_{i,t+n}=0\}}]}{R_{f,t}^{(n)}} \quad (22)$$

where the covariance captures a risk compensation for holding default risk, $\mathbb{E}_t[\mathbb{I}_{\{V_{i,t+n}=0\}}]$ is the expected actual probability of default and $R_{f,t}^{(n)}$ the risk-free rate. Since defaults tend to

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

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 or if discount rates are low.

Similarly, the value of the recovery rate can be written as

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

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 drift equals 0.0007 quarterly. Similarly, the volatility states, $\sigma(s_t) \in \{\sigma_1, ..., \sigma_5\}$, are chosen such that its standard deviation equals 0.000006 quarterly.

Regarding the preference parameters of the representative agent, we assume relative risk aversion (γ) of 10, an elasticity of intertemporal substitution (ψ) of 2 and rate of time preference (β) 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 τ is 15% as in Bhamra, Kuehn, and Strebulaev (2009).

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 120 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 quantitive 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 persistent enough. 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. 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

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 (2007).

Table 3 illustrates that the corporate nancing 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 de ned 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 de nition 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 rms.

3.4 Credit Spreads

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 4

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 (2009), 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 5, 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 101 basis points relative to 103 basis points in the data. For 10 year debt, the model implied credit spread is 114 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 1.24% of firms default and over a 10 year horizon 2.56% 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.

To gain a better understanding of mechanism driving credit spreads, we use the decomposition provided in Equations (21) to (23). Figure 2 displays actual default probabilities, $p_{i,t}^{(\tau)} = \mathbb{E}_t[\mathbb{I}_{\{V_{i,t+\tau}=0\}}]$, as a function of capital (left graphs) and total debt liabilities (right graphs). The two top graphs show results for τ = 5 year maturity debt and the two bottom graphs for τ = 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 the price of an Arrow-Debreu claim, $\xi_{i,t}^{(\tau)}$ that pays one

unit of consumption in the case of default as a function of capital (left graphs) and total debt liabilities (right graphs). Finally, Figure 4 displays credit spreads, $s_{i,t}^{(\tau)}$ as a function of capital (left graphs) and total debt liabilities (right graphs).

Decomposition (21) shows that credit spreads increase in the value of Arrow-Debreu claims that pay one unit of consumption in the case of default. These Arrow-Debreu claims, on the other hand, increase in actual default probabilities and a risk compensation for bearing default risk but decrease in the risk-free rate. Figure 2 illustrates that a higher capital level lowers default probabilities but that more debt liabilities raise default probabilities which is an intuitive result. Moreover, actual 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 booms but decrease over time in recessions. The same conclusions hold for the value of Arrow-Debreu default claims as shown in Figure 3. Figure 4 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.

3.5 Determinants of Credit Spreads and Default Probabilities

While Tables 5 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 determinants of spreads, and similarly, for the determinants of default probabilities. Tables 6 and 7 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.

Table 6 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 speci cation. While the rst univariate regression of credit spreads on market leverage shows that, as expected and in line with the empirical evidence, leverage is an important and signi cant determinant of credit spreads, the ensuing regressions suggest that variables capturing information about rms' investment opportunities and aggregate risk also come up as signi cant determinants. Tobin's Q, the investment-to-asset ratio as well as asset growth all contain information

about firms' investment behavior. While all these variables are significant determinants of spreads, the fact that they enter with a positive sign is more noteworthy. Broadly, an 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 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. Accordingly, firms with high Tobin's Q 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. Another way of seeing this, is to note that high Tobin's Q points to high investment opportunities going forward, which firms will want to exploit. In a setting with financing frictions and particularly with a tax advantage, firms will optimally choose to finance at least parts of their investment expenditures using debt. High investment opportunities and investment spending therefore forecast higher leverage in the future, and consequently higher default probabilities going forward, which will naturally be reflected in the prices of medium and long term corporate bonds. Interestingly, proxies for investment opportunities appear to contain valuable information about future leverage beyond current leverage. This is noteworthy, as by construction, standard structural models of corporate bond pricing by assuming exogenous variation in assets typically imply that current leverage is one of the most powerful predictors of future leverage, and hence default probabilities and credit spreads. The same intuition applies to the results concerning asset growth and investment-to-asset ratios as these quantities equally capture investment opportunities. The last two regressions in Panel A show that aggregate volatility σ_t also appears as a significant determinant of credit spreads, even controlling for leverage. This has an straightforward in the light of the credit risk premia inherent in credit spreads. As discussed earlier, the quantitative success of our model is due to the large credit risk premium it generates. Time-variation in aggregate volatility implies time variation in the market price of risk and therefore time variation in the credit risk premium. Equivalently, time variation in aggregate volatility implies time variation in risk neutral default probabilities. Naturally therefore, aggregate volatility determines credit spreads with a positive sign, which also reflects that in our setting aggregate volatility is countercyclical.

To the extent that investment opportunities reflect future financing choices and hence long-

term corporate bond prices, one would expect that this link is inherently tied to aggregate macroeconomic conditions. Indeed, aggregate investment is strongly procyclical, as is Tobin's Q and related measures of investment opportunities. In a similar vein, a growing literature reports strongly cyclical patterns in firms' financing choices with leverage typically displaying countercyclical movements. It is therefore natural to assume that the determinants of credit spreads are inherently conditional on macroeconomic conditions. Panels B and C investigate this hypethesis 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 Tobin's Q, which is followed by high investment rates and high asset growth rates. Again, high investment rates in our setting imply high financing needs, which predicts higher leverage in the future and consequently higher default probabilities in the future which would drive up credit spreads. One would therefore expect the positive link between proxies for investment opportunities and credit spreads is 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 much stronger determinants of credit spreads in long booms than across the cycle. This can also be understood in the context of the asset composition intuition developed above. 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. On the other hand, in booms, aggregate volatility appears to be a quantitatively less important predictor of spreads, again reflecting the countercyclical nature of volatility.

These effects are reversed in samples containing long recessions. In such samples, proxies for investment opportunities predict credit spreads negatively, and in turn, aggregate volatility becomes a very powerful predictor of credit spreads. While the second effect has a straightforward intuition - credit risk premia are higher in recessions due to the countercyclical movements in aggregate volatility - the first derives from the interplay between investment and default options. In bad times, assets in place rather than growth options are risky, in line with value effects in equity returns. 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 asymmetric modeling of investment and disinvestment options, specifically, disinvesting is more expensive than investing, which drives the negative impact of Tobin's Q on credit spreads. Overall therefore the effect of investment options on credit spreads is 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.

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 7, 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.

In Table 8, we report results on a set of regressions in a model specification where aggregate volatility is held constant. This helps to disentangle to what extent extent the results are driven by the assumption of time-varying volatility, and hence time-varying risk premia. The tables show that qualitatively all of our results obtain as well in this case. Consistent with the fact that relative volatility is higher in good times now, and relatively lower in bad times, the results in booms are exacerbated while those in recessions are somewhat mitigated.

3.6 Investments 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 9, we regress next quarter's aggregate investment growth, I_{t+1}, on the aggregate credit spread, s_t,

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

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 9 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 9 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 9 shows that the risk neutral credit spread looses its ability to forecast future investment growth. This nding 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 nancing and investment decisions.

4 Conclusion

Recent years have seen considerable research on credit risk and corporate bond pricing. In spite of these e orts, 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 signi cantly improved by accounting for rms' investment options. While state-of-the-art structural bond pricing models take the evolution of rms' assets as exogenously given, recent empirical evidence suggests tight links between real investment and credit spreads.

Using a tractable model of rms' investment and nancing decisions we show that the link between leverage and credit spreads is signi cantly 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 rms are risky in expansions because of the call feature of their growth options, high-leverage value rms 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 rms' assets and their relationship to aggregate risk is crucial for understanding credit spreads.

We document these patterns in a dynamic model of rm investment and nancing 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 114 bp spread for 10 year bonds from BBB rms, 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 exible 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 realistically model an asymmetry between rms' growth and disinvestment options, 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 therefore 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 nancial frictions when explaining corporate policies.

Our results thus suggest that understanding rm-level credit spreads requires accounting for rms' 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 rms' investment and nancing 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

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

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

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

and the stationary value function $v(k_t, b_t, s_t, x_t)$ solves

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

where

$$
x_t = g + \mu^x(s_{t-1}) + \sigma^x(s_{t-1})\varepsilon_t
$$

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

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

$$\begin{aligned}
d_t &= e_t - \quad (e_t) \\
e_t &= \pi_t + \tau\delta e^{-\Delta x_t} k_t - i_t + b_{t+1} - (1 + (1-\tau) r_t) e^{-\Delta x_t} b_t - \quad (\delta_t) \\
\pi_t &= (1-\tau)\left[\left(e^{-\Delta x_t}\right)^{\alpha} k_t^{\alpha} - e^{-\Delta x_t} k_t f\right] \\
(e_t) &= \lambda e_t \mathbb{I}_{\{e_t<0\}} \\
(\delta_t) &= \phi \delta_t \mathbb{I}_{\{\delta_t \neq 0\}} \\
\delta_t &= \frac{\quad_t}{X_t} = \left|b_{t+1} - e^{-\Delta x_t} b_t\right| \\
k_{t+1} &= (1-\delta) e^{-\Delta x_t} k_t + i_t
\end{aligned}$$

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

$$\begin{aligned}
B_{t+1} &= (1 + c_{t+1}) B_{t+1} \mathbb{E}_t\left[M_{t,t+1}\mathbb{I}_{\{V_{t+1}>0\}}\right] + \mathbb{E}_t\left[M_{t,t+1} R_{t+1} \mathbb{I}_{\{V_{t+1}=0\}}\right] \\
b_{t+1} &= (1 + c_{t+1}) b_{t+1} \mathbb{E}_t\left[m_{t,t+1}\mathbb{I}_{\{v_{t+1}>0\}}\right] + \mathbb{E}_t\left[m_{t,t+1} e^{\Delta x_{t+1}} r_{t+1} \mathbb{I}_{\{v_{t+1}=0\}}\right] \\
&= \left(1 + \frac{1}{1-\tau}\left(\frac{l_{t+1}}{b_{t+1}} - 1\right)\right) b_{t+1} \mathbb{E}_t\left[m_{t,t+1}\mathbb{I}_{\{v_{t+1}>0\}}\right] + \mathbb{E}_t\left[m_{t,t+1} e^{\Delta x_{t+1}} r_{t+1} \mathbb{I}_{\{v_{t+1}=0\}}\right] \\
b_{t+1} &= \frac{\mathbb{E}_t\left[m_{t,t+1}\left(\frac{1}{1-\tau} l_{t+1} \mathbb{I}_{\{v_{t+1}>0\}} + e^{\Delta x_{t+1}} r_{t+1} \mathbb{I}_{\{v_{t+1}=0\}}\right)\right]}{1 + \frac{\tau}{1-\tau}\left(\mathbb{E}_t\left[m_{t,t+1}\mathbb{I}_{\{v_{t+1}>0\}}\right]\right)}
\end{aligned}$$

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 o 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 gure displays investment growth and the default spread for the US economy. We use quarterly real private xed investments. The default spread is the di erence between Moody's BBB and AAA. The data spans the period 1955.Q1-2009.Q2.

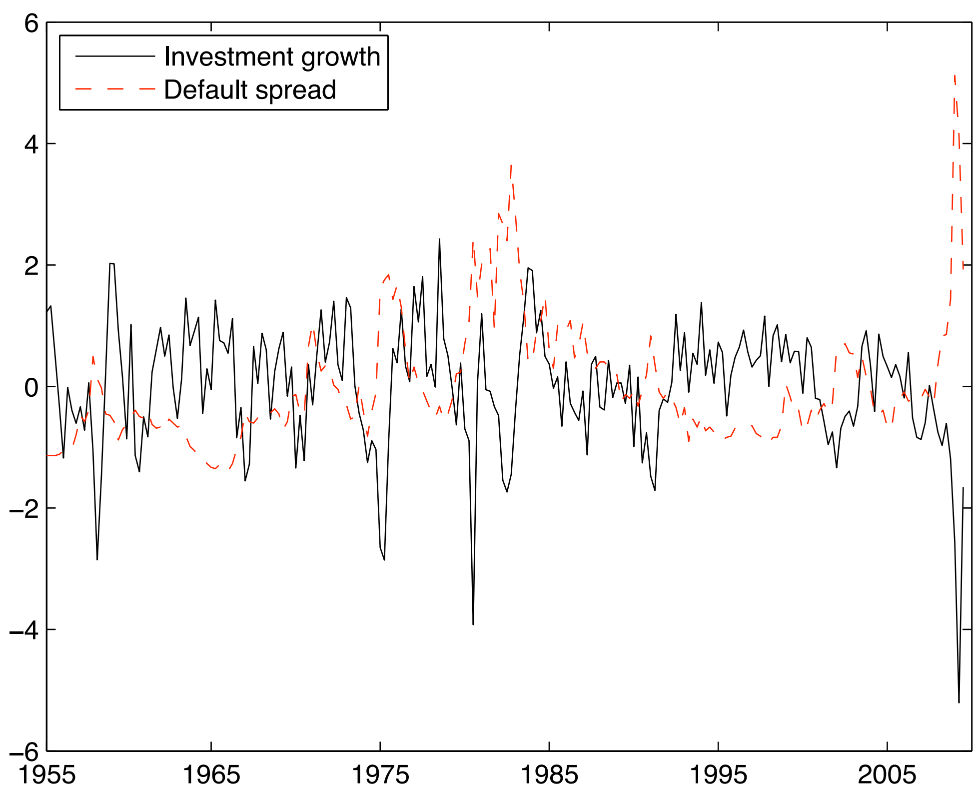

Figure 2: Actual Default Probabilities

This gure 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.

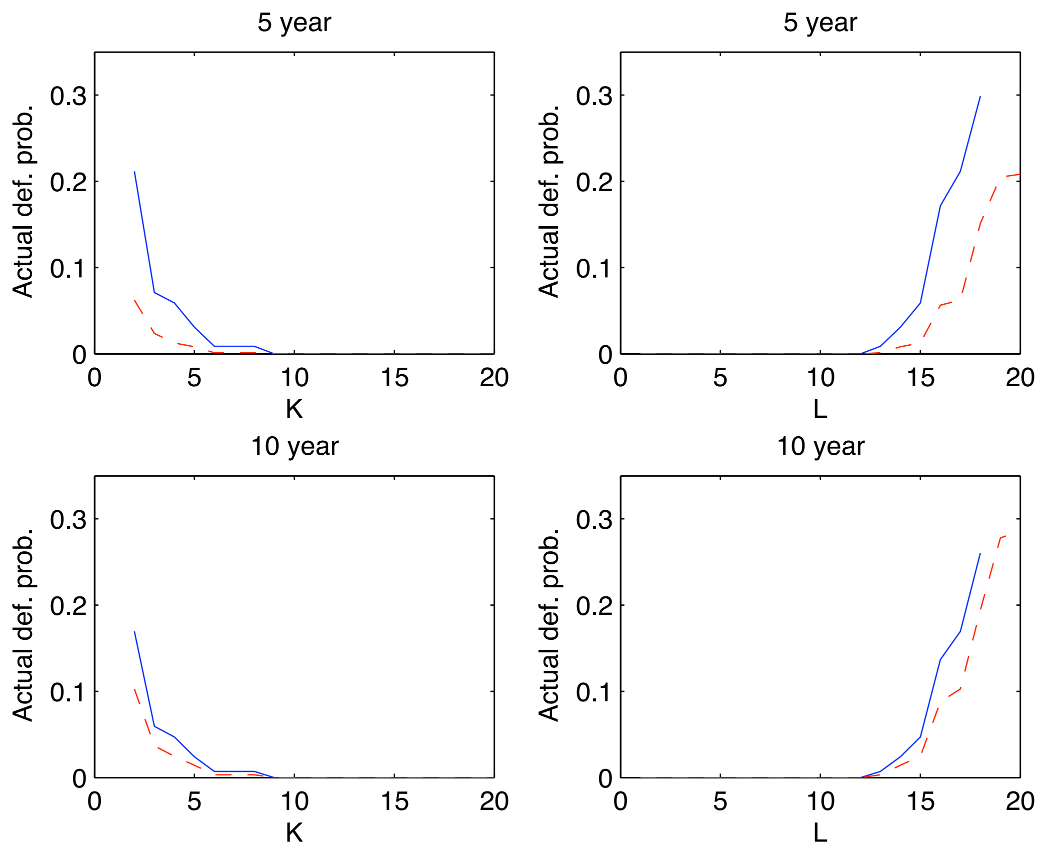

Figure 3: Arrow-Debreu Claims of Default

This gure displays the price of an Arrow-Debreu claim that pays one unit of consumption in the case of default 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.

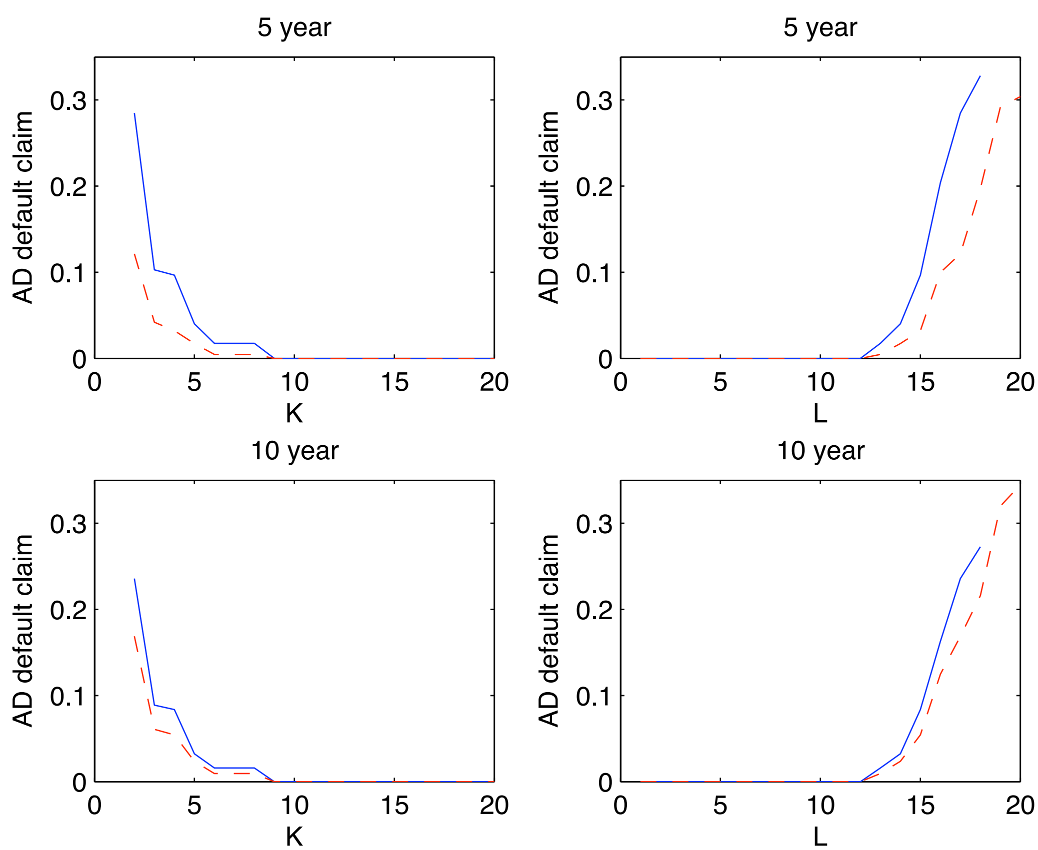

Figure 4: Credit Spreads

This gure 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.

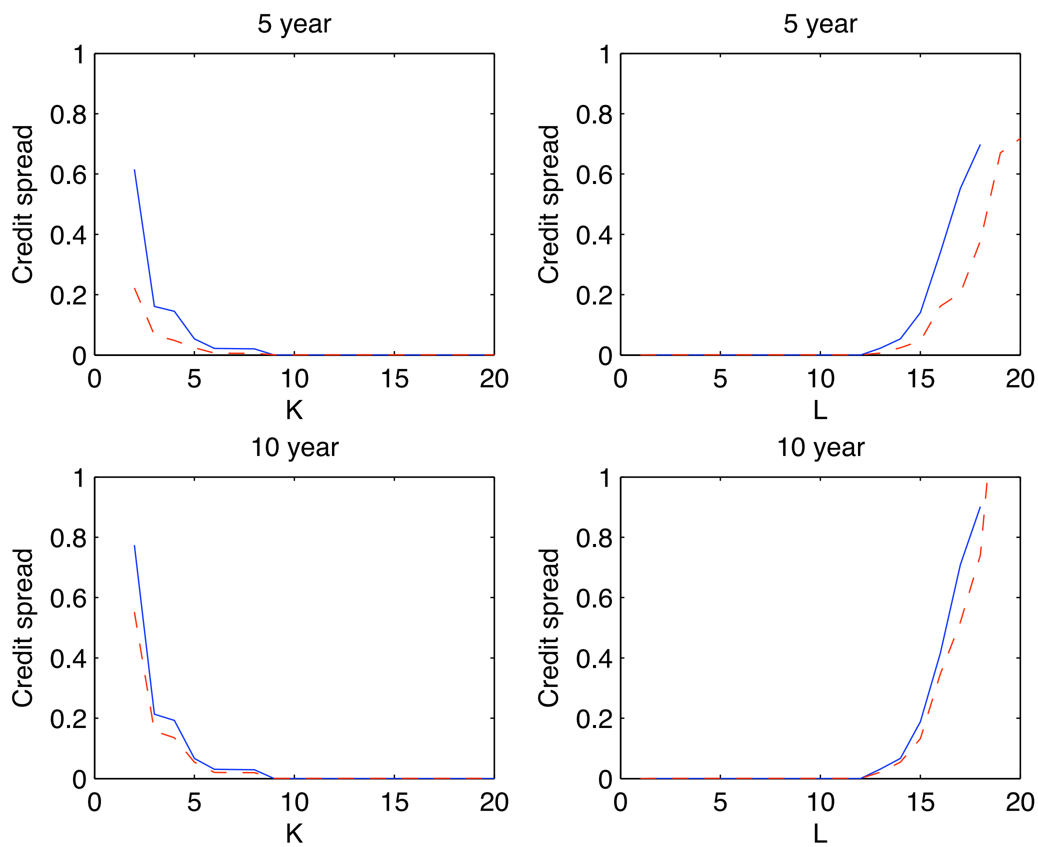

Table 1: Calibration

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

Description	Parameter	Value
Rate of time preference	β	0.995
Relative risk aversion	γ	10
Elasticity of intertemporal substitution	ψ	2
Growth rate of consumption	g	0.005
Capital share	α	0.65
Depreciation of capital	δ	0.03
Proportional costs of production	f	0.02
Adjustment costs parameter if $I > 0$	θ_+	0.1
Adjustment costs parameter if $I < 0$	θ_-	0.15
Corporate tax rate	τ	0.1
Equity issuance costs	λ	0.02
Debt issuance costs	ϕ	0.02
Bankruptcy costs	ξ	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 rms. This table shows cross simulation averages. The data are from Hennessy and Whited (2007), Davydenko and Strebulaev (2007) and Covas and Den Haan (2007).

Moment	Data	Model
Avg. annual investment to asset ratio	0.130	0.074
Volatility of investment to asset ration	0.006	0.030
Frequency of equity issuances	0.099	0.125
Avg. new equity to asset ratio	0.042	0.135
Avg. market to book ratio	1.493	1.976
Volatility of market ot book ratio	0.230	0.266
Book leverage	0.587	0.690
Market leverage	0.367	0.374

Table 4: 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 rms as reported by Cantor, Emery, Ou, and Tennant (2008). The rst row shows mean historical default rates for the period 1920{2007 and the second row for 1970{2007. Panel B reports the di erence between average spreads for BBB and AAA corporate debt, sorted by maturity. Data from Du ee (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
Du ee (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 5: Credit Market Statistics

In this table, we report average 5 and 10 year credit spreads and the corresponding actual default probabilities. For this exercise, we simulate 1,000 economies for 100 years each consisting of 3,000 rms. This table shows cross simulation averages.

Moment	Unit	Data	Model
5 year credit spread	b.p.	103.00	101.45
5 year default probability	%	1.83	1.24
10 year credit spread	b.p.	130.00	114.49
10 year default probability	%	4.35	3.56

Table 6: Credit Spread Determinants

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 rms. Panel A reports regressions from unconditional simulations, including booms and recessions as generated by our shock speci cation. 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	3.12	1. 72	1.99	2.16	1.67	1.52

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Table 7: Default Probability Determinants

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	4.05	2. 34	2.69	2.50	1.51	1.42
	(2.56)	(2.13)	(2.09)	(2.38)	(2.15)	(2.29)
Q		0.71				0.63
		(2.32)				(2.05)
$\frac{I}{K}$			1.02			
			(2.27)			
K				1.81		
				(2.14))		
σ					84.20	74.58
					(2.37)	(2.58)
Panel B: Booms						
Leverage	1.89	1.23	1.17	1.48	1.57	1.36
	(2.02)	(2.13)	(2.10)	(2.21)	(2.42)	(2.27)
Q		1.74				1.45
		(2.46)				(2.09)
$\frac{I}{K}$			1.80			
			(2.35)			
K				2.11		
				(2.31)		
σ					40.61	28.22
					(2.26)	(2.45)
Panel C: Recessions						
Leverage	6.29	6.87	5.17	5.96	3.25	3.68
	(2.62)	(2.34)	(2.49)	(2.39)	(2.67)	(2.24)
Q		-1.35				-1.14
		(-2.15)				(-2.10)
$\frac{I}{K}$			-1.08			
			(-2.07)			
K				-1.93		
				(-2.18)		
σ					132.71	110.38
					(2.51)	(2.73)

Table 8: Spread and Default Determinants with Constant Aggregate Volatility
The table reports logit regressions of default probabilities and credit spread regressions, in model simulations. We restrict attention to a model speci cation where aggregate volatility is constant. The dependent variable is the 1-year default probability, or the 5 year credit spread respectively. The regression results are obtained from simulations of 1,000 economies for 50 years each consisting of 3,000 rms. Panel A reports regressions from unconditional simulations, including booms and recessions as generated by our shock speci cation. 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						
	Credit Spreads			Default Probabilities		
Leverage	2.92	1.12	1.35	3.17	1.77	1.87
	(2.23)	(2.35)	(2.27)	(2.48)	(2.12)	(2.31)
Q		1.30			1.14	
		(2.18)			(2.17)	
$\frac{I}{K}$			1.56			1.44
			(2.05)			(2.26)
Panel B: Booms						
	Credit Spreads			Default Probabilities		
Leverage	1.82	1.33	1.46	2.97	2.11	2.26
	(2.36)	(2.24)	(2.13)	(2.49)	(2.22)	(2.37)
Q		1.31			1.16	
		(2.15)			(2.32)	
$\frac{I}{K}$			1.41			1.54
			(2.34)			(2.06)
Panel C: Recessions						
	Credit Spreads			Default Probabilities		
Leverage	3.59	4.12	4.02	5.47	5.16	5.35
	(2.75)	(2.21)	(2.28)	(2.68)	(2.45)	(2.30)
Q		-0.51			-0.72	
		(-2.03)			(-2.17)	
$\frac{I}{K}$			-0.64			-0.88
			(-2.16)			(-2.25)

Table 9: Aggregate Investment and Credit Spreads

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

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

In the data, we use quarterly real private xed investments and the aggregate credit spread is the di erence 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 rms. We run the same regression in the data and on simulated data. The risk neutral credit spread is the di erence 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.

	α	β	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)	