Investment-Based Corporate Bond Pricing

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ABSTRACT

A standard assumption of structural models of default is that firms assets evolve exogenously. In this paper, we examine the importance of accounting for investment options in models of credit risk. In the presence of financing and investment frictions, firm-level variables that proxy for asset composition are significant determinants of credit spreads beyond leverage and asset volatility, because they capture the systematic risk of firms’ assets. Cross-sectional studies of credit spreads that fail to control for the interdependence of leverage and investment decisions are unlikely to be very informative. Such frictions also give rise to a realistic term structure of credit spreads in a production economy.

JEL Classification: E22, E44, G12, G31, G32, G33.

Keywords: Real investment, dynamic capital structure, default risk, credit spreads, recursive preferences, macroeconomic risk.

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Electronic copy available at: https://ssrn.com/abstract=1929830
Quantitative research on corporate 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.\(^1\) This optimality condition implies that leverage and asset volatility are key determinants of credit spreads. These predictions have met only limited success empirically.\(^2\)

A key assumption of current structural models of default is that the evolution of firms’ asset values is given exogenously. This modeling approach follows the tradition of Modigliani and Miller (1958) where perfect financial markets allow the separation of financing and investment decisions. In this paper, we document the importance of accounting for the endogeneity of firms’ assets and thus investment decisions in models of credit risk. Exercising investment options changes a firm’s asset composition and the riskiness of its assets.

Recent literature shows that realistic credit spreads arise as compensation for exposure to macroeconomic risk.\(^3\) Credit spreads can be decomposed into expected losses in default and a credit risk premium, as empirically corporate defaults tend to cluster in recessions. In a model with aggregate risk and financial market imperfections, we show that asset composition affects credit risk beyond leverage and asset volatility. While asset volatility captures the total risk of firms’ assets, asset composition proxies for their systematic risk as growth options and assets in place have different exposure to aggregate risk over the business cycle. In other words, the systematic risk of firms’ assets and leverage are important determinants of the cross-section of credit risk premia.

We provide a tractable dynamic model to examine the links between credit risk, leverage, and investment across the business cycle. Our model highlights that in a world with capital market imperfections, financing and investment must be jointly determined. When debt is used to finance capital spending, asset expansions and changes in asset composition are generally correlated with leverage. This interdependence of financing and investment decisions, and thus of leverage and total and systematic asset risk, makes cross-sectional studies of credit risk challenging. We examine the empirical evidence through the lens of our model.
While we build on the recent literature relating firms’ capital structures to their investment policies (Hennessy and Whited (2005, 2007)), we introduce Epstein-Zin (1989) preferences with time-varying macroeconomic risk in consumption and productivity in a cross-sectional production economy to price risky corporate debt. 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 is what leads firms to issue debt, in our model it is the availability of real investment options. We assume that firms jointly choose leverage and investment to maximize equity value. Firms can default on their outstanding debt when the option to default is more valuable than paying back bond holders. When making these dynamic decisions, firms face fixed and proportional debt and equity issuance costs.

Our paper makes three sets of contributions. First, our model quantitatively rationalizes the empirical term structure of credit spreads in a production economy. As Huang and Huang (2012) point out, 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 government bonds. While Hackbarth, Miao, and Morellec (2006), Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), and Chen (2010) demonstrate that credit risk premia are compensation for macroeconomic conditions, production economies place considerably tighter restrictions on this link. A model without real and financial frictions renders corporate debt almost riskless since firms can use corporate policies to avoid default.

Quantitatively, our model generates a realistic credit spread of 101 basis points for five-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 firms face real and financing frictions. Capital is firm specific and thus the resale value is zero. In a model without disinvestment costs, firms would rarely choose to default because they would sell capital to pay off their debt. Essentially, the value of the disinvestment option drives out the value of the default option. In addition, costly debt adjustment and equity issuance costs increase the option value of defaulting.

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Second, we measure credit spreads in the cross-section of firms as in Bhamra, Kuehn, and Strebulaev (2010). Cross-sectional heterogeneity in asset composition and leverage raise the average credit spread because the values of both the investment and default option are convex functions of the state variables.

Second, we provide empirical evidence on the firm-level determinants of the cross-section of credit spreads and use our model to interpret the results. In line with the model’s predictions, we find that asset composition is a significant determinant of credit spreads beyond leverage and asset volatility. This result is consistent with the notion that the cross-section of credit spreads reflects differences in credit risk premia. Unconditionally, we find that value and small firms exhibit higher spreads. When we control for leverage and asset volatility, we see that growth firms tend to have higher credit spreads. Intuitively, growth options come into the money in expansions so their assets have more systematic risk than value firms, which derive most of their value from assets in place. Value firms, however, have more collateral and higher leverage, thus driving up credit spreads. Empirically, this suggests that value effects in credit spreads may be due in large part to leverage. From a modeling perspective, the results highlight the importance of allowing for dynamic capital structure and debt financing of growth option exercise. Theoretically, the results suggest that when capital market imperfections render financing and investment decisions correlated, unconditional links are likely uninformative. Moreover, the results suggest that both value and size effects in credit spreads reflect cross-sectional differences in credit risk premia.

Third, from a modeling point of view, we numerically solve and analyze a dynamic model with multiperiod, finite maturity defaultable debt. Doing so is computationally challenging, but adds an important piece of realism to the class of models we consider. Most of the extant literature on dynamic financing and investment in discrete time relies on one-period debt to preserve tractability. A number of papers exploit continuous-time methods that allow one to characterize finite-maturity debt. We adapt their approach in a flexible discrete-time setup.

A. Related Literature

Our paper is at the center of several converging lines of literature. To begin with, our
objective is to link structural models of default and financing with the literature on growth options and firm investment. In this regard, our paper is related to Miao (2005), Sundaresan and Wang (2007), Bolton, Chen, and Wang (2011), and Hackbarth and Mauer (2012). However, contrary to our work, these papers do not focus on the pricing of corporate bonds and do not consider the importance of macroeconomic conditions. Barclay, Morellec, and Smith (2006), Chen and Manso (2010), and Arnold, Wagner, and Westermann (2013) also explore the effects of growth options on credit risk. These papers consider a levered firm that finances a single growth option exclusively with equity. While this environment allows one to obtain analytic solutions, we quantitatively investigate credit spreads when firms can fully dynamically optimize their investment and capital structure decisions.

The paper by Arnold, Wagner, Westermann (2013) is especially close to our work, as they also consider a setup with time-varying macroeconomic risk and a stochastic discount factor based on Epstein-Zin (1989) preferences. In contrast to our study, however, they do not test their empirical predictions and do not examine the cross-section of credit risk premia. While analytically less tractable, our numerically solved model suggests that accounting for multiple growth and refinancing options is empirically relevant. Indeed, we show that allowing for joint dynamic capital structure and investment decisions significantly improves the model’s ability to quantitatively and qualitatively capture the time series and cross-section of credit spreads.9

Our paper is also 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), Carlson and Lazrak (2010)). Motivated by the credit spread puzzle, that is, the observation that standard structural models of corporate finance in the tradition of Merton (1974) are unable to rationalize the historical levels of credit spreads once calibrated to historical default and recovery rates (see Huang and Huang (2012)), this literature stresses 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 corporate financing policies. While the literature
considers endowment economies only, our analysis highlights that frictions to adjusting firm assets are a crucial determinant of default decisions and therefore credit spreads. Moreover, we examine the notion that risk premia constitute a significant fraction of credit spreads in the cross-section.

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 (Gomes (2001)) is motivated by the cash-flow sensitivity of corporate investment and considers reduced-form representations of the costs of external finance, more recent work considers fully fledged capital structure choices, allowing for leverage, default, and equity issuance (e.g., Cooley and Quadrini (2001), Moyen (2004), and Hennessy and Whited (2005, 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 literature considers 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 the level and time-variation of credit spreads can be 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 (e.g., Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), and Zhang (2005)) successfully relates anomalies in the cross-section of stock returns such as the value premium to firms’ investment policies. Another recent line of research focuses on the link between firms’ financing decisions and stock returns (some recent papers include Garlappi and Yan (2011), Livdan, Sapriza, and Zhang (2009), and Gomes and Schmid (2010)). By relating risk premia in corporate bond prices to firms’ investment and financing policies, our work here is complementary.

I. Model
The model consists of two building blocks: a stochastic discount factor, which we derive from a representative household and an aggregate consumption process, and a cross-section of heterogenous firms, which make optimal investment and financing decisions given the stochastic discount factor.

We assume that 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 levels and dynamics for the market price of risk. Firms choose optimal investment to maximize their equity value. Investment is financed by retained earnings as well as equity or debt issuances. Firms can default on their outstanding debt if prospects are sufficiently bad.

We emphasize that we do not close the model in general equilibrium. We find it convenient to specify a consumption-based stochastic discount factor to discipline its calibration using consumption data. We make no additional assumptions about the link between aggregate dividends, which are endogenous in the model, and consumption, which is exogenous, other than they are affected by the same aggregate states.

A. Stochastic Discount Factor

The representative agent maximizes recursive utility over consumption, $C_t$, following Epstein and Zin (1989). The preference parameters of an Epstein-Zin agent are the rate of time preference, $\beta \in (0, 1)$, the elasticity of intertemporal substitution (EIS), $\psi$, and the coefficient of relative risk aversion (RRA), $\gamma$. These preferences provide a separation between preference for consumption smoothing over time (EIS) and across states (RRA) as well as preference for 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 time-varying drift and volatility,

$$C_{t+1} = C_t \exp\{g + \mu_c(\omega_t) + \sigma_c(\omega_t)\eta_{t+1}\},$$  \hspace{1cm} (1)

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

The Epstein-Zin (1989) stochastic discount factor is given by

\[
M_{t,t+1} = \beta^\theta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \left( \frac{S_{t+1} + 1}{S_t} \right)^{-(1-\theta)},
\]

(2)

where \( S_t \) denotes the wealth-consumption ratio and \( \theta = \frac{1-\gamma}{1-1/\psi} \). When \( \theta = 1 \), the stochastic discount factor 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 RRA (\( \psi > 1/\gamma \)), the agent prefers that intertemporal risk due to the Markov chain be resolved sooner rather than later.

In an economy driven solely 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, that is, \( S_t = S(\omega_t) \). Based on the Euler equation for the return on wealth, the wealth-consumption ratio vector \( S_t \) solves the system of nonlinear equations defined by

\[
S_t^\theta = \mathbb{E}_t \left[ \beta^\theta \left( \frac{C_{t+1}}{C_t} \right)^{1-\gamma} (S_{t+1} + 1)^\theta \right].
\]

(3)

The \( n \)-period risk-free rate is given by \( R_{f,t}^{(n)} = 1/\mathbb{E}_t[M_{t,t+n}] \).

**B. 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

\[
\Pi_{i,t} = (1 - \tau)(Z_{i,t}X_t^{1-\alpha} K_{i,t}^\alpha - K_{i,t} f),
\]

(4)

where \( Z_{i,t} \) is an idiosyncratic shock, \( X_t \) is an aggregate 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 \( f \geq 0 \) the proportional costs of production. An important implication of a capital share less than unity is that firms possess a sequence of growth options that are decreasing in firm size.
The aggregate productivity shock $X_t$ follows a random walk with time-varying drift and volatility,

$$X_{t+1} = X_t \exp\{g + \mu_x(\omega_t) + \sigma_x(\omega_t)\eta_{t+1}\},$$

(5)

where $\mu_x(\omega_t)$ and $\sigma_x(\omega_t)$ depend on the aggregate state of the economy and $\eta_{t+1}$ are the same standard normal shocks as in the consumption process. The $i$-th firm-specific productivity shock $Z_{i,t}$ follows mean-reverting process

$$\ln Z_{i,t+1} = \rho_z \ln Z_{i,t} + \sigma_z \varepsilon_{i,t+1}$$

(6)

with persistence $\rho_z$ and volatility $\sigma_z$. The assumption that $\varepsilon_{i,t+1}$ is firm specific requires that

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

Firms 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

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

(7)

where $\delta > 0$ denotes the depreciation rate of capital. We model real options by assuming that investment is irreversible, that is,

$$I_{i,t} \geq 0.$$  

(8)

C. Financing

Corporate investment as well as any distributions can be financed with either internal funds generated by operating profits or new issues, which can take the form of debt (net of repayments) or equity. Following Hackbarth, Miao, and Morelec (2006), we model finite-maturity debt via sinking funds provisions. We denote by $B_{i,t}$ the book value of outstanding liabilities that firm $i$ has outstanding at time $t$ and $P_{i,t}$ the per unit market price of these liabilities. Corporate bonds pay a fixed coupon $c$ in every period and a fraction $\kappa$ is paid back each period (after payment of the coupon). The average maturity of these bonds thus
corresponds to $\frac{1}{\kappa}$ periods. Denoting new bond issuance by $J_{i,t} \geq 0$, the amount of corporate bonds evolves according to

$$B_{i,t+1} = (1 - \kappa)B_{i,t} + J_{i,t}. \quad (9)$$

When firms change the amount of debt outstanding, they incur a cost. We define debt adjustment costs in terms of new bond issuances, $J_{i,t}$. Firms face fixed and proportional debt adjustment costs denoted by $\phi_0$ and $\phi_1$, respectively. Formally, these costs are given by

$$\Phi(J_{i,t}) = \phi_{0,t}I_{\{J_{i,t} > 0\}} + \phi_1 J_{i,t}, \quad (10)$$

where the indicator function $I_{\{J_{i,t} > 0\}}$ implies that these costs apply only when the firm is raising new debt.

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

$$\Lambda(E_{i,t}) = (\lambda_{0,t} + \lambda_1|E_{i,t}|)I_{\{E_{i,t} < 0\}}, \quad (11)$$

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

Investment, equity payout, and financing decisions must satisfy the budget constraint

$$E_{i,t} = \Pi_{i,t} + \tau \delta K_{i,t} - I_{i,t} - ((1 - \tau)c + \kappa)B_{i,t} + P_{i,t}J_{i,t} - \Phi(J_{i,t}), \quad (12)$$

where again $E_{i,t}$ denotes the equity payout. Note that the 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,

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

D. 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, that is, 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 long-term debt.

We can now characterize the problem facing equity holders, taking payments to bond holders as given. The value of these payments will be determined endogenously below. Shareholders jointly choose investment, \( I_{i,t} \), and new bond issuances, \( J_{i,t} \), to maximize the equity value of each firm, which can then be computed as the solution to the dynamic program

\[
V_{i,t} = \max \left\{ 0, \max_{I_{i,t},J_{i,t}} \left( D_{i,t} + \mathbb{E}_t [M_{t+1}V_{i,t+1}] \right) \right\},
\]

where the expectation on the left-hand side is taken by integrating over the joint conditional distributions of aggregate and idiosyncratic shocks. Note that the first maximum captures the possibility of default at the beginning of the current period, in which case shareholders will get nothing.\(^{13}\) Finally, aside from the budget constraint embedded in the definition of dividends, \( D_{i,t} \), firms face the irreversibility constraint (8), debt issuance costs (10), and equity issuance costs (11).

\section*{E. 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. The market value of debt must satisfy the Euler condition

\[
P_{i,t} = \mathbb{E}_t \left[ M_{t+1} \left( (1 - \mathbb{I}_{V_{i,t+1}=0})(c + \kappa + (1 - \kappa)P_{i,t+1}) + \mathbb{I}_{V_{i,t+1}=0} \frac{W_{i,t+1}}{B_{i,t+1}} \right) \right],
\]

where \( W_{i,t+1} \) denotes the recovery on a bond in default and \( \mathbb{I}_{V_{i,t+1}=0} \) is an indicator function that takes the value of one when the firm defaults and zero when it remains active. Following Hennessy and Whited (2007), creditors are assumed to recover the fraction of the firm’s current assets and profits net of liquidation costs. Formally, the default payoff is equal to

\[
W_{i,t} = (1 - \xi)((1 - \tau)\Pi_{i,t} + (1 - \delta)K_{i,t}),
\]

where \( \xi \) measures the proportional loss in default.
F. Credit Spreads

Credit spreads are defined as the yield difference between defaultable and default-free debt

\[ s_{i,t} = \frac{\kappa + c}{P_{i,t}} - \frac{\kappa + c}{P^*_{i,t}}, \]  

(17)

where \( P^*_{i,t} \) is the price of default-free debt

\[ P^*_{i,t} = \mathbb{E}_t \left[ M_{t,t+1} \left( (c + \kappa + (1 - \kappa) P^*_{i,t+1}) \right) \right]. \]  

(18)

To gain some intuition about the drivers of credit spreads, for simplicity we now consider the case in which all debt matures next period, by setting \( \kappa = 1 \). For this special case, the bond pricing Euler equation (15) simplifies to

\[ P_{i,t} = (1 + c) \mathbb{E}_t \left[ M_{t,t+1} \left( 1 - I_{\{V_{i,t+1}=0\}} \right) \right] + \mathbb{E}_t \left[ M_{t,t+1} I_{\{V_{i,t+1}=0\}} \frac{W_{i,t+1}}{B_{i,t+1}} \right]. \]

This bond pricing equation can be solved for the arbitrage-free bond yield,

\[ \frac{1 + c}{P_{i,t}} = \frac{1 - \chi_{i,t}}{\mathbb{E}_t[\{M_{t,t+1} \mid (1 - q_{i,t})]}, \]  

(19)

where \( q_{i,t} \) is the risk-neutral default probability and \( \chi_{i,t} \) is the value of the recovery rate

\[ R_{i,t+1} = W_{i,t+1}/(B_{i,t+1} P_{i,t}), \]

defined by

\[ q_{i,t} = \mathbb{E}_t \left[ \frac{M_{t,t+1}}{\mathbb{E}_t[\{M_{t,t+1} \mid I_{\{V_{i,t+1}=0\}}}} \right], \quad \chi_{i,t} = \mathbb{E}_t \left[ M_{t,t+1} R_{i,t+1} I_{\{V_{i,t+1}=0\}} \right]. \]

Given (17) and (19), the log credit spread can be approximated by

\[ \log s_{i,t} \approx q_{i,t} - \chi_{i,t}. \]  

(20)

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

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

\[ q_{i,t} = p_{i,t} + \text{Cov}_t \left( \frac{M_{t,t+1}}{\mathbb{E}_t[\{M_{t,t+1} \mid I_{\{V_{i,t+1}=0\}}}}, I_{\{V_{i,t+1}=0\}} \right), \]  

(21)
where the actual default probability is defined as \( p_{i,t} = \mathbb{E}_t[\mathbb{I}_{\{V_{i,t+1} = 0\}}] \) and the covariance captures risk compensation for default risk. Since defaults tend to occur in bad times when marginal utility is high, this 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

\[
\chi_{i,t} = \frac{\mathbb{E}_t[R_{i,t+1}\mathbb{I}_{\{V_{i,t+1} = 0\}}]}{R_{f,t}^{(1)}} + \text{Cov}_t(M_{t,t+1}, R_{i,t+1}\mathbb{I}_{\{V_{i,t+1} = 0\}}).
\]

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

We can thus think of the (log) credit spread as a combination of two terms. The first component captures expected losses in default, \( p_{i,t} - \mathbb{E}_t[R_{i,t+1}\mathbb{I}_{\{V_{i,t+1} = 0\}}]/R_{f,t}^{(1)} \), while the second one, \( \text{Cov}_t(M_{t,t+1}/\mathbb{E}_t[M_{t,t+1}], \mathbb{I}_{\{V_{i,t+1} = 0\}}) - \text{Cov}_t(M_{t,t+1}, R_{i,t+1}\mathbb{I}_{\{V_{i,t+1} = 0\}}) \), is a risk premium. We refer to the latter component as the credit risk premium. This decomposition shows that credit spreads depend on both historical and risk-neutral default probabilities as well as recoveries rates. While historical default probabilities depend on firms’ total, and thus idiosyncratic, credit risk, risk-neutral default probabilities crucially depend on systematic credit risk as governed by the covariation of default rates and losses with the stochastic discount factor. The empirical evidence on historical default rates and recoveries places tight bounds on the contribution of idiosyncratic credit risk to spreads, suggesting that credit risk premia make up a substantial fraction of credit spreads.

II. Empirical Results

In this section, we present the quantitative implications of our model by means of calibration and simulation, and evaluate them empirically using data on credit default swaps. Since the model does not entail a closed-form solution, we solve it numerically. The numerical procedure is detailed in the Appendix. In the following, we first describe our data and explain our calibration strategy. We then provide numerical and empirical results.
A. Data

We use data on corporate policies from Compustat, equity market data from CRSP, and data on credit spreads from CMA Datavision, as we now describe in more detail.

Similar to Leary and Roberts (2005), we use quarterly Compustat data for the period 1984 to 2011. Debt is measured as current liabilities (DLCQ) plus long-term debt (DLTTQ). Using CRSP data, market equity is the product of share price (PRC) and number of shares outstanding (SHROUT) for companies with ordinary common shares (SHRCD 10 or 11). Leverage is defined as debt divided by debt plus market equity. The market-to-book ratio is the ratio of debt plus market equity to total assets (ATQ). Profitability is the ratio of operating income before depreciation (OIBDPQ) to assets.

Investments are capital expenditures (CAPXY) net of sales of property, plant, and equipment (SPPEY). The investment rate is the ratio of investments to the gross capital stock (PPEGTQ) if this rate exceeds 1%. Equity issuances are sales of common and preferred stock (SSTKY) net of purchases (PRSTKPCY). An equity or debt issuance is defined as having occurred in a given quarter if the net equity issuance or change in debt, normalized by assets at the end of the previous period, is greater than 1%. Variables that are reported as year-to-date are transformed to quarterly flow variables based on the fiscal year-end (FYR).

We exclude companies if their primary SIC is between 4900 and 4999, between 6000 and 6999, or greater than 9000, as the model is inappropriate for regulated, financial, or public service firms. We also restrict the sample to firms with strictly positive book equity (CEQQ), sales (SALEQ), and leverage.

As a measure of credit risk, we use credit default swap (CDS) data from CMA Datavision. Mayordomo, Pena, and Schwartz (2010) find that the CMA database leads the price discovery process in comparison with other CDS databases including Markit. We focus on five-year credit spreads as they are the most liquid for the 2004 to 2011 period. The CMA data set covers on average 320 firms per year. We match CDS with CRSP-Compustat data at a quarterly frequency using end-of-quarter observations.

B. Calibration
Our quarterly calibration is summarized in Table I. Regarding the preference parameters of the representative agent, we assume RRA ($\gamma$) of 7.5, an EIS ($\psi$) of 2, and rate of time preference ($\beta$) of 0.996, which are common values in the asset pricing literature to generate a realistic market price of risk. This parameterization implies that the representative agent has a preference for early resolution of uncertainty, so that she dislikes negative shocks to expected consumption growth and positive shocks to consumption volatility.

For the calibration of the consumption process, we follow Bansal, Kiku, and Yaron (2012). They assume that the first and second moments of consumption growth follow two separate processes. For tractability, we model the aggregate Markov chain, $\omega_t$, to jointly affect the drift and volatility of consumption growth and to consist of five states. To calibrate the Markov chain, we follow the procedure suggested by Rouwenhorst (1995). Since there is no mapping from the monthly calibration of Bansal, Kiku, and Yaron (2012) to the quarterly frequency, we simulate quarterly consumption growth rates and aggregate them to the annual frequency. The persistence of the Markov chain, the drift states $\mu(\omega_t) \in \{\mu_1, ..., \mu_5\}$, and the volatility $\sigma(\omega_t) \in \{\sigma_1, ..., \sigma_5\}$ of consumption growth are chosen to match annual consumption growth moments as reported in Bansal, Kiku, and Yaron (2012). As a result, we set the persistence of the Markov chain to 0.95, the mean and volatility of the drift states to zero and 8.69e-4, respectively, and the mean and volatility of variance states to 1.51e-4 and 1.05e-5, respectively.

At the firm level, we calibrate the volatility ($\sigma_z$) and persistence ($\rho_z$) of the idiosyncratic productivity process to match the cross-sectional dispersion in leverage and profitability. The drift ($\mu_x(\omega_t)$) and volatility ($\sigma_x(\omega_t)$) of aggregate productivity scale with the respective moments of consumption growth by a factor of 2.7. This value allows us to roughly match the equity and value premia as well as the volatility of both aggregate stock returns and the aggregate log price-dividend ratio.

We set the capital share ($\alpha$) of production equal to 0.65 in line with the evidence in Cooper and Ejarque (2003). Capital depreciates ($\delta$) 3% per quarter as in Cooley and Prescott (1995).
Firms face proportional costs of production \( (f) \) of 0.04, similar to Gomes (2001).

Firms can also issue debt and equity. Andrade and Kaplan (1998) report default costs of about 10% to 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 \( (\xi) \) to 20%. The effective corporate tax rate \( (\tau) \) is 14%, consistent with the evidence in van Binsbergen, Graham, and Yang (2010). When firms issue new debt or equity they face proportional and fixed costs. We set these costs to match the size and frequency of new issuances. In general, our parameter choices are consistent with Gomes (2001), Hennessy and Whited (2007), and Altinkilic and Hansen (2000).

In our baseline calibration, we consider corporate debt with a maturity of five years. This is achieved by setting \( \kappa = 0.05 \). In extensions, we also consider 10-year debt \( (\kappa = 0.025) \) and one-year debt \( (\kappa = 0.25) \).

Most of our quantitative results are based on simulations. Rather than repeating the simulation procedure, we summarize it here. Our empirical targets are based on two data sets that do not cover the same sample periods. Quarterly CRSP-Compustat data span almost 30 years, whereas the data sample on credit default swaps is relatively short and includes the Great Recession of 2008/2009, arguably an extreme episode in terms of both macroeconomic performance and credit risk. To account for this difference, we evaluate the quantitative implications using two samples. The first sample, which we refer to as the long sample, is intended to capture the generally more stable episode of 1984 to 2011, which our CRSP-Compustat data cover. Note that this sample covers the episode often labeled as the Great Moderation because of its low aggregate volatility. We therefore simulate 3,000 firms over 28 years (after dropping 200 initial periods), and repeat the procedure 100 times. The second sample, which we refer to as the short sample, is intended to mimic the macroeconomic performance around the financial crisis. This latter sample allows us to directly compare the simulated data to our empirical results on credit spreads. We therefore simulate 320 firms for eight years, and repeat the procedure 100 times. We randomly draw 320 firms from the distribution of the long sample and then restart the economy at the lowest aggregate state. In
all simulations, defaulting firms are replaced with newborn firms, which have a small capital stock and zero leverage, such that the mass of firms is constant over time.

C. Aggregate Moments

In Table II we report unconditional aggregate moments of consumption growth and asset prices generated by our model. The table shows cross-simulation averages of annual consumption growth, its volatility and autocorrelation, average risk-free rate and risk-free rate volatility, average equity and value premia, volatility of the log price-dividend ratio, aggregate stock return volatility, skewness, and kurtosis, as well as average firm-level stock return volatility. All moments are annualized. Consumption, risk-free rate, equity premium, and price-dividend ratio data are from Bansal, Kiku, and Yaron (2012). Aggregate stock return volatility, skewness, and kurtosis are based on the CRSP value-weighted index, the value premium is based on the Fama-French (1993) HML factor, and average stock return volatility is based on quarterly CRSP data for the years 1984 to 2011.

[INSERT TABLE II HERE]

Our calibration of the Markov model (1) for consumption growth is largely consistent with the data. In the model, annual consumption growth has an average of 1.2%, a volatility of 2.4%, and an autocorrelation of 39.8%, which are very close to the calibration in Bansal, Kiku, and Yaron (2012). The average unconditional risk-free rate generated by the model is similar in the data but is not sufficiently volatile. In the model, the risk-free rate changes with the state of the Markov chain and the high EIS causes a very stable risk-free rate over time.

The model also generates fairly large equity and value premia of 7.2% and 4.0%, respectively. The magnitude of both premia is driven by the persistence of the aggregate Markov state and the preference for early resolution of uncertainty as captured by the wedge between the EIS and inverse of RRA. The sign of the value premium is due to leverage. In our model, this comes from both operating leverage, as illustrated by Carlson, Fisher, and Giammarino (2004), and financial leverage, as discussed in Gomes and Schmid (2010).14
As pointed out by Chen, Collin-Dufresne, and Goldstein (2009), credit spreads are very sensitive to the ratio of aggregate to idiosyncratic risk. If most of the cash flow risk is driven by aggregate risk, then credit spreads even in the Merton model are sizable. Yet in the data, average firm volatility is approximately twice the level of market volatility. In our model, the ratio of average firm volatility to market volatility is 1.8 relative to 1.9 in the data. Similarly, it is also important to match the skewness and kurtosis in market returns, coming from jumps in the pricing kernel. Counterfactually large jumps at the firm and aggregate levels inflate credit spreads. Our model generates aggregate stock return skewness and kurtosis of −0.8 and 5.1, respectively, which are close to their empirical counterparts.

D. Corporate Policies

We now illustrate the model’s quantitative implications for optimal firm behavior. In Table III, we report unconditional moments of optimal corporate policies generated by the model. This table shows cross-simulation averages of the average quarterly investment-to-asset ratio and its cross-sectional dispersion, the frequency and size of new equity and bond issuances, average market-to-book ratio, average market leverage and its cross-sectional dispersion, and average profitability and its cross-sectional dispersion. The data are from the quarterly CRSP-Compustat file as explained above.

[INSERT TABLE III HERE]

Table III illustrates that the corporate financing and investment policies are generally consistent with the data. Because of capital depreciation, the model is able to replicate the average investment-to-asset ratio. The tension between volatile idiosyncratic shocks and the option value of waiting to invest renders a realistic dispersion in cross-sectional investment-to-asset ratios. Firms can finance capital expenditures through equity and bond issuances. In the data, equity issuances are less frequent than bond issuances but they are larger in magnitude. The model achieves a similar pattern by assuming larger fixed costs but smaller proportional costs of equity relative to bond issuances. The average market-to-book ratio
or Tobin’s Q, defined by $Q = (V + PB)/K$ in the model, is related to the curvature in the production function as well as the investment and default options. Without the default option, the market-to-book ratio would be lower and closer to the data. Proportional production costs and volatile idiosyncratic shocks help to explain the average profitability, measured as $\Pi/K$, and its dispersion.

Since the goal of this paper is to generate a realistic time series and cross-section of credit spreads, it is important that the model-implied leverage ratios are compatible with empirical estimates. To this end, we report average leverage and its dispersion in Table III and study the cross-sectional distribution of leverage in Table IV. Market leverage is defined as the ratio of the value of outstanding debt relative to the market value of the firm, $L = PB/(PB + V)$. In the model, average market leverage and its dispersion are close to empirical estimates.

Given the substantial tax benefits to debt, generating realistically low leverage ratios is often challenging for structural models of credit risk, an observation referred to as the low-leverage puzzle. In our setup with macroeconomic risk as well as financial and investment frictions, firms optimally choose low leverage in order to preserve borrowing capacity for bad times.

We now examine the model’s implications for the cross-sectional distribution of leverage. Following Rajan and Zingales (1995), we look at the popular regressions used in the empirical capital structure literature relating corporate leverage to several financial indicators. Specifically, we run a pooled panel regression of leverage on log size, measured by $\log(K)$, the market-to-book ratio, profitability, asset volatility, and the aggregate log price-dividend ratio. We follow Davydenko and Strebulaev (2007) and compute asset volatility as the leverage-weighted average of one-year stock return and bond return volatility using monthly data. Bond prices and returns are imputed from CDS spreads.

[INSERT TABLE IV HERE]

Table IV summarizes our findings. The table reports empirical estimates for both the long sample (1984 to 2011) and the short sample (2004 to 2011) because CDS data became available only recently. The table documents the positive relation between firm size and leverage in
the long sample. In our model with dynamic capital structure, large firms have accumulated more capital over time, which they financed partially with debt. Similarly, operating leverage through fixed costs of production renders small firms more risky, so that they use financial leverage more prudently. Because of decreasing returns to scale, growth options are relatively more important for small firms, so that growth firms have low leverage in our model in line with the empirical evidence. Table IV also shows that our model is able to reproduce the observed negative relationships between leverage and either profitability or Q. With persistent shocks, profitable and high Q firms have large investment opportunities going forward, which they finance with equity at the margin. Since equity issuances are costly, such firms borrow prudently to avoid flotation costs.15

While the impact of firm characteristics on leverage is well known, our framework also implies that firm-specific and aggregate risk measures impact leverage decisions. In particular, in our model firms optimally lower leverage when the volatility of their assets increases as in the data. Leverage is also cyclical and rises in times of aggregate risk when the price-dividend ratio is low.

The fact that leverage varies with the business cycle suggests that all corporate policies are cyclical. In Table V, we illustrate firms’ cyclical behavior by means of simple correlations of average firm policies with aggregate output growth. In the data, we use the growth rate of real GDP from the National Income and Product Accounts reported by the Bureau of Economic Analysis and the aggregate U.S. corporate default rate from Standard & Poors.

[INSERT TABLE V HERE]

While in our one-factor economy the correlations are, not surprisingly, a little high, in qualitative terms the model broadly replicates firms’ cyclical behavior rather well. In line with the data, investment growth is strongly procyclical. Investment expenditures raise firms’ needs for external financing, which, given the tax advantage of debt, will come through a mix of equity and debt issuance. This makes both equity and debt issuance procyclical as well. While firms will also issue equity and additional debt to cover financing shortfalls in
downturns, investment opportunities are sufficiently procyclical to be the dominating effect. In contrast, market leverage is countercyclical in the model because equity risk premia are sufficiently countercyclical. Countercyclical leverage renders defaults more likely in bad times.

E. Term Structure of Credit Risk

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

It is well known that standard structural models of corporate default, such as Merton (1974) or Leland (1994), fail to explain observed credit spreads given low historical default probabilities. This fact is first documented in Huang and Huang (2012) and is typically referred to as 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 large compensation for holding default risk in terms of a credit spread. For instance, the historical default rate of BBB-rated firms is 1.95% over a five-year horizon but the yield of BBB-rated firms relative to AAA-rated firms is 103 basis points. At a 10-year horizon, the yield spread increases to 131 basis points and the cumulative default probability to 4.90%.

To gauge whether our model generates realistic credit spreads, we consider evidence from simulated panels of firms as explained above. Table VI summarizes our findings. We report average equally weighted credit spreads, actual default rates, and leverage for our benchmark model (Model I). In Panel A, we consider a long sample designed to match the historical evidence on credit spreads, while a shorter sample (Panel B) mimics the more recent macroeconomic performance that our empirical CDS data set reflects. We then vary the debt maturity parameter and report results from economies in which debt is short-term (Panel C) and long-term (Panel D), holding all other parameters fixed at the benchmark level. This allows us to examine the effects of debt maturity on credit spreads and default rates.

[INSERT TABLE VI HERE]

For our benchmark specification with five-year debt, our model generates a credit spread of 107 basis points relative to 103 basis points in the data (Panel A). At the same time,
actual default rates are small. Over a five-year horizon, on average approximately 2% of firms
default, as in the data. Similarly, the model matches quite well the credit spreads in our
empirical sample, which includes the recent Great Recession. The average CDS rate for the
period 2004 to 2011 is 160 basis points while our model generates 165 basis points in the short
sample (Panel B). Default rates in this sample are only somewhat higher than in the data.

Three economic mechanisms drive these results in our investment-based model. First,
the model generates investment, financing, and, most importantly, default policies of firms
that are consistent with the empirical evidence. As we 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 adjustment costs.

Second, cross-sectional heterogeneity in asset composition and leverage raise the average
credit spread because the value of both the investment and the default options are convex func-
tions of the state variables. Importantly, these effects are stronger under the risk-neutral than
the physical probability measure, coming from Epstein-Zin (1989) preferences and Markov
switching dynamics for the aggregate state. In other words, accounting for cross-sectional
variation in firm characteristics is quantitatively important as the aggregate credit spread is
especially sensitive to the mass of firms with high credit risk. A common approach in the
corporate bond pricing literature is to study corporate policies 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 capital structures every period. Similar
to Bhamra, Kuehn, and Strebulaev (2010), we study credit spreads in the cross-section of
firms.

Third, as default rates are strongly countercyclical, investors require risk premia on de-
faultable bonds. Our model with time-varying macroeconomic risk and recursive preferences
generates credit risk premia and a countercyclical market price of risk, allowing the model
to be consistent with the historical evidence on credit spreads. Importantly, time-varying
volatility makes credit risk premia time-varying and countercyclical as well.
Turning to debt maturity, we find that credit spreads and default rates are naturally increasing with maturity. For 10-year debt (Panel D), the model generates a credit spread of 126 basis points relative to 130 basis points in the data, with a cumulative default rate of 4.42%, slightly less than in the data. Interestingly, even with one-year debt (Panel C) the model-implied credit spread amounts to 45 basis points with a cumulative default rate of 0.16%, suggesting that even at the short end of the term structure the model generates a substantial risk premium embedded in corporate bond prices. Yet these results also suggest that the term structure of spreads in the model is somewhat too flat.

It is important to keep in mind that changing debt maturity affects all moments of firm policies, and especially leverage. Shortening debt maturity makes refinancing and hence deleveraging in downturns easier, so that firms optimally lever up more, thus raising the credit spread, all else equal. Similarly, even when debt is short term, corporations still have considerable exposure to sudden shifts in macroeconomic regimes, as parameterized by our aggregate Markov chain. In contrast, lengthening debt maturity makes refinancing more difficult, in response to which leverage falls below its empirical counterpart. The net effect is a modest increase in credit spreads and default rates with increasing maturity.

F. Frictions and the Term Structure of Credit Risk

We now discuss the sensitivity of the model implied-credit spreads with respect to a number of important modeling choices. In particular, we quantify the dependence of our results on real and financial frictions. Table VI reports credit spreads, default rates, and leverage for our benchmark model (Model I) along with four other 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. Model III removes the investment irreversibility constraint, that is, making investment completely reversible, but it retains financial transaction costs. Model IV removes both investment irreversibility and transaction costs. Model V retains irreversibilities and financing frictions, but removes real frictions in the form of operating leverage, that is, proportional costs of production $f$.

We focus on the benchmark case with five-year debt maturity (Panel A). The table shows
that the results on credit spreads and default probabilities are sensitive to the underlying model of investment and financing. Removing financial transaction costs, although small in magnitude, reduces the five-year spreads by 33 basis points (Model II). Qualitatively, this result is intuitive. Removing equity issuance costs makes it cheaper for firms to roll over existing debt and cover cash shortfalls by issuing new equity, and removing debt adjustment costs makes it cheaper to delever. In the Internet Appendix, we show that equity – not debt – adjustment costs is the key financial friction. This points to the quantitative relevance of the firm’s budget constraint, which ties the availability of investment options to the availability of external financing in our model. In fact, without equity flotation costs, the cross-sectional dispersion of firms in model simulations is unrealistically small and too few firms are close to default.

Model III shows that removing any obstructions to downward adjustment of the capital stock decreases the five-year spread by almost 50 basis points. When investment is reversible firms can delever very effectively by selling off their capital stock, which will naturally reduce default risk. Model IV shows that removing both disinvestment and financing obstructions reduces the spread by another eight basis points. Quantitatively, these results suggest that disinvestment obstructions have stronger effects on spreads than refinancing frictions. In contrast, Model V shows that reducing operating leverage by means of removing proportional costs of production has the strongest quantitative effects on spreads, more than halving the five-year spread relative to the benchmark case. Removing these proportional costs increases profit margins, makes firms larger, and alleviates exposure to idiosyncratic and aggregate cash flow risks, thus reducing credit risk.

Intuitively, one would guess that removing any investment and refinancing friction would drive credit spreads essentially down to zero. However, removing such obstructions affects credit risk in two ways that work in opposite directions. On the one hand, firms increase leverage when they face fewer frictions as this allows them to take advantage of the debt tax shield more easily. All else equal, this drives up default probabilities and credit spreads. Indeed, as reported in the table, leverage ratios are increasing across the model specifications.
On the other hand, firms will lever up more in expansions, anticipating that they will be able to delever quickly in bad times. This effect makes leverage more volatile and reduces the countercyclicality of market leverage and default probabilities. This mechanism will work to reduce credit spreads through the risk premium channel: default rates become less correlated with consumption growth and risk premia fall. Indeed, controlling for expected losses, the risk premium component in spreads decreases. Therefore, firms’ exposure to macroeconomic risk is directly linked to the magnitude of the frictions they face. Removing frictions allows firms to smooth cash flows and reduces risk premia.

In sum, these results suggest that in a production economy various ingredients are necessary to rationalize the historical evidence of credit spreads, namely, financial and real frictions. Financial frictions involve equity issuance and debt adjustment costs, and real frictions involve obstructions to the downward adjustment of the capital stock as well as operating leverage arising from proportional costs of production. We next show that these frictions are also relevant for generating novel cross-sectional patterns in credit spreads.

G. Cross-Section of Credit Risk

Sufficient cross-sectional variation in firm characteristics is important to quantitatively rationalize the time-series properties of aggregate credit spreads. We now empirically and quantitatively examine the cross-sectional determinants of credit spreads through the lens of our model.

As in other structural models of credit risk, the critical statistic determining default probabilities and thus credit spreads is a firm’s distance to default, which depends not only on a company’s leverage but also on the volatility of its assets. Relative to the extant literature, however, our analysis highlights two mechanisms. First, when credit risk premia make up a substantial part of credit spreads, cross-sectional variation in credit spreads also reflects differences in exposure to macroeconomic risk. In other words, our model predicts that not only is the distance to default a critical determinant of credit spreads, but also its covariance with the stochastic discount factor. Second, from the point of view of a model with capital market imperfections, firms’ assets, their volatility, and, importantly, their composition are
endogenous and jointly determined with leverage.

A long literature on the cross-section of stock returns emphasizes that cross-sectional differences in risk premia are intimately connected to variation in asset composition. For example, value firms, which derive most of their value from assets in place, earn higher average returns than do growth firms, whose value depends mostly on growth options. To the extent that such differences capture differential exposure to macroeconomic risk, this suggests that value companies’ performance is more highly correlated with aggregate risk. All else equal, this exposure raises the covariation of a firm’s distance to default with the stochastic discount factor, which in turn increases credit spreads. On the other hand, a firm’s exposure to systematic risk may reflect asset risk, leverage, or both. Understanding the joint determination of investment and financing policies thus has important empirical implications for the cross-section of credit spreads.

We thus expect that beyond leverage and asset volatility, asset composition should be an important determinant of credit spreads. While asset volatility is a measure of a firm’s total risk, asset composition captures differential exposure to systematic macroeconomic risk, both of which affect credit spreads. If a firm’s asset volatility is entirely idiosyncratic, this will be reflected only in expected losses, while if that same asset volatility is entirely systematic, it will require a large credit risk premium on top of that. It is thus important to disentangle the two effects.

We follow the literature on the cross-section of stock returns and capture exposure to macroeconomic risk by means of firm characteristics such as size, market-to-book, and price-dividend ratios. We start by documenting empirical evidence on the links between credit spreads, leverage, and these variables by means of sorts and cross-sectional regressions.

G.1. Sorts

Table VII, Panel A reports univariate quintile sorts of credit spreads based on firm characteristics, namely, market leverage, book leverage, market-to-book ($Q$), and size (market capitalization). Panel A corresponds to the empirical sample covering five-year CDS rates
between 2004 and 2011, both at the quarterly frequency and annualized. Not surprisingly, credit spreads are monotonically increasing across the market leverage quintiles. However, the relationship also exhibits a striking nonlinearity. While in the lower leverage quintiles credit spreads are somewhat flat, credit spreads almost triple from the fourth to the highest leverage quintile. This observation confirms that accounting for cross-sectional heterogeneity in spreads is an important determinant of the average credit spread. A similar pattern is evident in book leverage sorts, although the cross-sectional dispersion is somewhat less pronounced, likely because book leverage is less volatile. More importantly, the next column documents that credit spreads are clearly decreasing in market-to-book. Value firms, with more assets in place and fewer growth options (as measured by market-to-book) have larger credit spreads. This pattern also exhibits a nonlinearity in that the effect is strongest in the lowest market-to-book quintile, although the nonlinearity is not as pronounced as in the market leverage sorts. Finally, credit spreads are also decreasing in firm size as measured by market capitalization.

[INSERT TABLE VII HERE]

Panel B of Table VII shows that our model is able to at least qualitatively replicate the sorts documented in the data. Generally speaking, the model generates somewhat less cross-sectional dispersion than in the data, reflecting a tension between matching default rates, which requires moderate proportional production costs and idiosyncratic volatility, and cross-sectional variation, which increases in proportional costs and idiosyncratic volatility. In contrast, the model picks up some of the nonlinearities in the data reasonably well.

From a modeling perspective, Panel B also highlights the importance of allowing for dynamic capital structure and debt financing of growth options in models of credit risk. Value firms have high credit spreads, unconditionally, because they financed their past investment partially with debt, and thus have higher leverage. It is well known (see, for example, Ozdagli (2012)) that real-options-based models of investment without dynamic capital structure or operating leverage predict a growth premium in stock returns. In the Internet Appendix, we
show that the same holds in credit spreads. Restricting growth options to be equity financed implies a growth premium in credit spreads.

The last two effects are reminiscent of value and size effects in the cross-section of stock returns. However, value and size premia in stock returns capture risk premia as compensation for differential exposure to macroeconomic risk, while credit spreads reflect both idiosyncratic as well as systematic factors. Below, in Section II.G.4., we use our model to examine the extent to which size and value effects capture credit risk premia.

While value firms with low book-to-market ratios have high credit spreads, empirically they also tend to have higher leverage, as documented in Table IV. It is thus important to consider the joint determination of credit spreads with assets and leverage. We now provide initial evidence on the links between credit spreads, leverage, and asset composition by means of double sorts.

Table VIII reports results of sorting credit spreads unconditionally along market-to-book and both book leverage (left panel of the table) and market leverage (right panel of the table). The book leverage sorts clearly document that credit risk is increasing in leverage and decreasing in growth options. In all book leverage terciles, credit spreads are monotonically decreasing in market-to-book. Moreover, the effects are strikingly nonlinear. Most of the credit risk is concentrated in the high leverage and low market-to-book segment. The differences in spreads between low and high market-to-book terciles are nonlinearly increasing in leverage. Similarly, the differences in spreads between high and low leverage terciles are nonlinearly decreasing in market-to-book.

[INSERT TABLE VIII HERE]

Turning to market leverage sorts, the sorting variables become increasingly correlated, leading to interesting nonmonotonicities. This is noteworthy, as in structural models of credit risk, shareholders optimally exercise their default option when the equity value drops too low. Accounting for the market value of this option is thus important, making market leverage the natural and appropriate variable capturing debt financing. While credit risk is still decreasing
in market-to-book in the low leverage terciles and most concentrated in the high leverage and low market-to-book segment, credit spreads are flattening in the mid leverage tercile and are slightly U-shaped in the high leverage tercile. Intuitively, in the low leverage portfolio the default option is not very valuable, so that high market-to-book mostly signals high growth opportunities going forward and less credit risk. On the other hand, in the high leverage tercile, default options become more valuable so that high market-to-book can signal both growth options and default options, making the unconditional link ambiguous, as the default options can drive out growth options. The model captures these regularities qualitatively reasonably well, although the dispersion in credit spreads across bins is somewhat lower than in the data.

**G.2. Panel Regressions**

We now examine the conditional link between credit spreads and measures of leverage and asset risk by means of cross-sectional regressions. Table IX reports pooled panel regressions for the years 2004 to 2011. The choice of explanatory variables is guided by our model, which holds that cross-sectional variation in credit spreads is due to differences in both idiosyncratic risk and exposure to macroeconomic risk. Besides leverage and asset volatility, which control for idiosyncratic firm risk, we also include as regressors market-to-book and log size to capture asset composition and thus exposure to macroeconomic risk. Finally, to control for aggregate market conditions, we include the aggregate log price-dividend ratio. \( t \)-statistics are clustered at the firm level and reported in parentheses.

[INSERT TABLE IX HERE]

The baseline specification (1) confirms that in line with structural models of credit risk, leverage and asset volatility are indeed significant determinants of credit spreads. This result survives upon inclusion of size and market-to-book, both of which enter significantly as well (specification (2)). This shows that market-to-book and size are economically important determinants of spreads. Size not surprisingly enters with a negative sign. More interestingly,
market-to-book \textit{conditionally} enters with a positive sign. While in unconditional univariate and double sorts with market leverage, credits spreads were decreasing in market-to-book conditional on leverage and asset volatility, high market-to-book firms, that is, growth firms, tend to have higher credit spreads. Finally, the aggregate price-dividend ratio enters significantly as well and, as expected, with a negative sign (specification (3)). Credit spreads increase in aggregate bad times when the price-dividend ratio is low. Importantly, both market-to-book and size effects are robust to the inclusion of the price-dividend ratio, which we interpret as evidence that these variables all carry information about exposure to macroeconomic risk.

In sum, these results suggest that both idiosyncratic and macroeconomic risk are priced significantly in the cross-section of credit spreads. More importantly, proxies for exposure to macroeconomic risk are significant determinants of credit spreads above and beyond the standard variables leverage and asset volatility.

The model qualitatively and sometimes quantitatively does a good job replicating our empirical findings. One thing to note is that the $R^2$s in our simulations are considerably higher than in the data. Apart from the fact that the model is obviously stylized, this is also because in the model we can explicitly compute asset volatility, while in the empirical work we need to resort to proxies given the lack of direct data on firm asset values.

We note that, as in the data, in the model market-to-book enters with a positive sign, \textit{conditional} on leverage and asset volatility. Within the model this has a simple intuition. Firms with a high market-to-book ratio derive a large fraction of their value from growth options. Growth options tend to come in the money in expansions, so that their payoffs are positively correlated with macroeconomic conditions. Conditional on leverage and total asset volatility, this makes growth firms riskier, as their distance to default is particularly procyclical. This is noteworthy as our sorts reveal that, unconditionally, value firms have higher leverage, so that on average value firms have higher credit spreads. This suggests that value effects may be largely driven by leverage. These results highlight the importance of accounting for the joint determination of investment and financing.

\textit{G.3. Frictions and the Cross-Section of Credit Risk}
To the extent that cross-sectional variation in credit spreads reflects firms’ differential exposure to macroeconomic risk, we expect the cross-sectional implications of our model to be sensitive to the specification of real and financial frictions. As documented above, removing frictions allows firms to alleviate their exposure to macroeconomic risk and reduces risk premia. We now quantitatively examine this dependence by running cross-sectional regressions in various model specifications, gradually removing real and financial frictions. Table X reports the results. As in Table VI, Model I refers to the benchmark model, Model II features no financial adjustment costs, Model III removes the irreversible investment constraint, and Model IV features neither financial nor real adjustment costs. Model V removes proportional costs of production but retains all other frictions.

[INSERT TABLE X HERE]

While leverage enters positively and significantly in all model specifications, the explanatory power of leverage is increasing in terms of $R^2$ when firms face fewer constraints. On the other hand, the additional explanatory power of asset volatility, as well as market-to-book and size, decrease across the model specifications. This suggests that in a model without financial transaction costs and real frictions, leverage largely becomes a sufficient statistic for credit spreads, with proxies for asset risk and volatility not adding much explanatory power. Thus, leverage effectively subsumes distance to default.

The intuition for this result is quite simple. Without real and financial adjustment costs, firms endogenously adjust leverage such that asset risk is largely offset by financial risk. Firms with high (low) asset risk choose optimally low (high) leverage. This holds for both total as well as systematic risk. In other words, firms target a leverage ratio that optimally balances their financing policy with the pricing consequences of their asset structure, given the preferential tax treatment of debt. Such a target leverage ratio is, of course, state dependent. In the absence of frictions, firms quickly adjust and approach the target leverage ratio. Quantitatively, the model predicts that asset composition will no longer affect credit spreads much and target leverage ratios subsume all the information about credit spreads. With frictions,
the adjustment will be slow and imperfect, giving rise to rich cross-sectional patterns in credit spreads.\textsuperscript{17}

We quantify this effect by means of target adjustment regressions, following Flannery and Rangan (2006). More specifically, we estimate

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

where $\chi$ 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 by the vector $X_{i,t}$. Importantly, this captures the state dependence of target leverage. In our case we include Tobin’s $Q$, size, and profitability. Consistent with the above intuition, we find that the speed of adjustment is decreasing in the magnitude of frictions. More frictions, real or financial, impede firms’ target adjustment and make leverage more persistent.

\textit{G.4. Cross-Sections of Credit Risk Premia and Stock Returns}

So far we empirically document a number of patterns in the cross-section of credit spreads. Using the model, we now examine the cross-section of credit risk premia and start by revisiting the link between size, value, and credit spreads to examine whether there is a value risk premium in credit spreads.

In Section II.G.1. we use univariate sorts to show that credit spreads decrease in market-to-book and size, reminiscent of value and size premia in stock returns. Table XI reports, in addition to the credit spreads on book-to-market- and size-sorted portfolios, the corresponding annualized default rates and credit risk premia from model simulations.\textsuperscript{18} Not surprisingly, default rates are clearly decreasing across market-to-book and size quintiles. However, more notably, so are credit risk premia. This is to say that small firms and value firms clearly default more often, but on top of that, they are more likely to default in bad macroeconomic conditions, giving rise to a higher credit risk premium. Our model thus suggests that the dispersion in credit spreads across size and market-to-book is partially explained by dispersion in risk premia, in much the same way as value and size premia in stock returns reflect
compensation for differential exposure to aggregate risk. Our model is also consistent with
the latter evidence, as documented by the last columns, reporting average stock returns of
the corresponding portfolios. These results are in line with the notion that asset composition
reflects exposure to macroeconomic risk.

[INSERT TABLE XI HERE]

Interestingly, the model predicts that the dispersion in credit risk premia across market-
to-book quintiles is higher than that across size quintiles. This result lines up nicely with the
observation that the spread in average stock returns is higher across market-to-book portfolios
than across size portfolios in the data. Although the return spreads are somewhat lower than
in the data, qualitatively our model replicates this pattern well. While the dispersion in
default rates is higher in the market-to-book sorts than in the size sorts, the opposite holds
for average losses on these portfolios, as recoveries on low market-to-book tend to be higher
than on small firms.

The previous sorts suggest a close link between credit spreads and stock returns. To the
extent that credit spreads reflect risk premia, we would generally expect the exposure to
macroeconomic risk in credit spreads to show up in stock returns as well. After all, firms de-
fault when equity values drop to zero, so that when the distance to default correlates strongly
with macroeconomic conditions, so will equity returns. On the other hand, all else equal,
idiosyncratic risk increases credit spreads, which affects stock returns through its effect on
leverage. In particular, if cross-sectional variation in credit spreads mostly reflects differences
in default probabilities through differences in idiosyncratic risk, one could imagine a negative
link between credit spreads and stock returns. Firms with high idiosyncratic risk would choose
low leverage and, assuming sufficiently small differences in asset risk, would end up leveraging
up their asset risk by less, therefore earning lower expected stock returns. The overall effect
of credit spreads on stock returns is thus not obvious. We examine this link by investigating
stock returns on portfolios sorted on firms’ credit spreads in our model.
The results are summarized in Table XII. In Panel A, we report average stock returns of univariate quintile portfolio sorts based on credit spreads. We find that stock returns increase in credit spread bins. This result is consistent with the above discussion in the sense that both average default rates and credit risk premia line up with stock returns. In Panel B, we sort firms into portfolios based on credit spreads and expected default rates and report average stock returns for each portfolio. Variation in credit spreads, holding expected default probabilities constant, should be largely due to differences in credit risk premia. Indeed, the link between stock returns and credit spreads becomes more pronounced. This corroborates the importance of distinguishing between expected losses and credit risk premia in credit spreads. Risk premia on stock returns reflect the covariation of equity values with the stochastic discount factor, just as credit risk premia reflect covariation of distance to default with the stochastic discount factor. In that respect, our model is consistent with and rationalizes recent empirical evidence on the links between credit risk and equity risk, such as Anginer and Yildizhan (2012) and Friewald, Wagner, and Zechner (2012).

[INSERT TABLE XII HERE]

III. Conclusion

Recent research has considerably advanced our understanding of credit risk. Notwithstanding these efforts, however, the empirical success of the leading class of corporate bond pricing models is rather limited in terms of explaining both the time series and the cross-section of credit spreads. While state-of-the-art structural bond pricing models take the evolution of firms’ assets as exogenously given in the spirit of Modigliani and Miller (1958), we argue and provide quantitative and empirical evidence that investment options are an important determinant of credit spreads.

We provide a tractable model of firms’ investment and financing decisions under aggregate risk where optimal firm decisions are distorted by financial market imperfections as well as
real investment frictions. As corporate defaults cluster in recessions, the model predicts a sizeable credit risk premium so that it delivers a realistic term structure of credit spreads while keeping actual default rates realistically low. Rationalizing the term structure of credit spreads in a production economy imposes tight restrictions on modeling both real and financial frictions. In the presence of these frictions, firms’ leverage will deviate from the target and asset composition becomes an important determinant of the cross-section of credit spreads beyond leverage and asset volatility. Asset composition captures firms’ systematic risk as growth options and assets in place have different exposure to aggregate risk over the business cycle, and hence determines firms’ credit risk premia.

When asset composition is a determinant of credit risk, the unconditional link between leverage and credit spreads is weak. The joint endogeneity of investment and financing can thus rationalize the weak empirical performance of structural bond pricing models. In this paper we take a step towards an integrated framework linking firms’ investment and financing decisions to the pricing of corporate bonds. The model makes novel empirical predictions for which we find support in the data.
NOTES


2Collin-Dufresne, Goldstein, and Martin (2001) show that structural models explain less than 25% of the variation in credit spread changes. Davydenko and Strebulaev (2007) reach a similar conclusion for the level of credit spreads. Similarly, it is well known that these models typically predict counterfactually low credit spreads; see Huang and Huang (2012).


4Similar 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.

5Jermann (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.

6In the Internet Appendix, available in the online version of the article on The Journal of Finance website, we show that the model would predict, among other things, a growth premium in credit spreads if growth options were restricted to be equity financed.

7In a contemporaneous paper, Gourio and Michaux (2012) also consider defaultable multiple-period finite maturity debt to examine the predictive power of credit spreads for corporate investment.

8See, for example, Leland and Toft (1998) and Hackbarth, Miao, and Morellec (2006).

9The Internet Appendix contains a number of robustness checks, including model specifications with both static capital structure and static investment decisions.

10In our quantitative work, we use a quarterly calibration, so that the average maturity corresponds to $\frac{1}{4}$. If productivity has a time trend, the fixed component is growing over time too. The same is true for the fixed equity issuance costs.

12See Gomes (2001) and Hennessy and Whited (2007) for a similar specification.

13In practice, there can be violations of the absolute priority rule, implying that shareholders in default still recover value. Garlappi and Yan (2011) analyze the asset pricing implications of such violations.

14The sign of the value premium is due to the fact that value firms are highly levered, as they financed their investment partially with debt in our model. It is well known that models with investment irreversibility but without financial and operating leverage predict a growth
premium; see Ozdagli (2012).

15In the Internet Appendix we illustrate the importance of dynamic capital structure and continuous investment choices for cross-sectional leverage regressions.

16The data on credit spreads are taken from Huang and Huang (2012) and historical default rates from Ou, Chiu, and Metz (2011).

17This is consistent with a number of recent papers stressing the importance of financial adjustment costs for capital structure dynamics, for example, Leary and Roberts (2005).

18We compute credit risk premia as the annualized difference between credit spreads and one-period-ahead expected losses.
We use numerical dynamic programming to obtain approximations to the equity value function (14) and the bond pricing function (15). To this end, we first need to transform the model to make it stationary. We can define the following stationary variables:

\[ k_{t+1} = \frac{K_{t+1}}{X_t}, \quad b_{t+1} = \frac{B_{t+1}}{X_t}, \quad d_t = \frac{D_t}{X_t}, \quad e_t = \frac{E_t}{X_t}, \quad i_t = \frac{I_t}{X_t}, \text{ and } j_t = \frac{J_t}{X_t}. \]

To save on notation, we drop the index \( i \) and ignore the default option in the following. Because of the homogeneity of the equity value function and the linearity of the constraints, we can rescale the equity value function (14) by \( X_t \):

\[
V \left( \frac{K_{t+1}}{X_t}, \frac{B_{t+1}}{X_t}, 1, Z_t \right) = D_t + \mathbb{E}_t \left[ M_{t,t+1} \frac{X_{t+1}}{X_t} V \left( \frac{K_{t+1}}{X_{t+1}}, \frac{B_{t+1}}{X_{t+1}}, 1, Z_{t+1} \right) \right],
\]

The stationary value function \( v(k_t, l_t, \omega_t, \omega_{t-1}, \eta_t, Z_t) \) solves

\[
v(k_t, b_t, \omega_{t-1}, \omega_t, \eta_t, Z_t) = d_t + \mathbb{E}_t \left[ M_{t,t+1} e^{\Delta x_{t+1}} v(k_{t+1}, b_{t+1}, \omega_t, \omega_{t+1}, \eta_{t+1}, Z_{t+1}) \right], \quad (23)
\]

where

\[
\Delta x_{t+1} = g + \mu_x(\omega_t) + \sigma_x(\omega_t) \varepsilon_{t+1}.
\]

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

\[
d_t = e_t - \Lambda(e_t)
\]

\[
e_t = \pi_t + \tau \delta e^{-\Delta x_{t+1}} k_t - i_t - ((1 - \tau)c + \lambda)e^{-\Delta x_{t+1}} b_t + P_i j_t - \Phi(j_t)
\]

\[
\pi_t = (1 - \tau) \left[ Z_t (e^{-\Delta x_t})^\alpha k_t^\alpha - e^{-\Delta x_t} k_t^\alpha f \right]
\]

\[
\Lambda(e_t) = (\lambda_0 + \lambda_1 |e_t|) I_{\{e_t < 0\}}
\]

\[
\Phi(j_t) = \phi_0 I_{\{j_t > 0\}} + \phi_1 j_t
\]

\[
b_{t+1} = (1 - \lambda)e^{-\Delta x_t} b_t + j_t
\]

\[
k_{t+1} = (1 - \delta)e^{-\Delta x_t} k_t + i_t.
\]

We can also rewrite the bond pricing equation (15) in terms of stationary variables, such that

\[
P_t = \mathbb{E}_t \left[ M_{t,t+1} \left( (1 - I_{\{V_{t+1} = 0\}})(c + \lambda + (1 - \lambda) P_{t+1}) + I_{\{V_{t+1} = 0\}} e^{\Delta x_{t+1}} \frac{w_{t+1}}{b_{t+1}} \right) \right], \quad (24)
\]
where the stationary recovery value in default is given by

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

The numerical dynamic programming approach is complicated by the joint determination of the stationary equity value function (23) and the stationary bond pricing function (24). We use an iterative procedure to jointly approximate these two functions on discrete grids.

Throughout the procedure, we create grids for the shocks and the endogenous state variables, $k_t$ and $b_t$. Given their persistent nature, we use the Rouwenhorst (1995) procedure to discretize the aggregate state and the firm-level technology shocks. The aggregate Markov chain has five states and changes in the technology shock are approximated with 11 elements. We create grids for capital and the number of bonds outstanding, each with 50 points. The choice vectors for tomorrow’s capital level and bonds each have 500 points.

We start our procedure by setting $\kappa = 1$, that is, by considering one-period debt. In this case, as shown by Gomes and Schmid (2010), the equity and bond value functions can be computed using a procedure that nests the determination of the bond market equilibrium in the equity value function, given suitable initial conditions. We thus use value function iteration to solve for the equity value function on the discretized state space, and find, after the equity value function converges, the bond pricing function from (24). While our focus is on five-year defaultable debt, the solutions in the one-period case provide a good initial condition for the more general case.

We next proceed by varying, step-by-step, the parameter governing the maturity of debt, $\kappa$. For $\kappa \neq 1$, the equity and bond pricing functions have to be found jointly. We start the iterative procedure by setting $\kappa = 1$. This gives us equity and bond value functions for that case, using the nested procedure above. We then decrease $\kappa$ and use the given equity and bond value functions as initial conditions. Given these initial conditions, we update the equity value function using the Bellman equation, (23), one step. We use the updated equity value function to update the bond pricing equation using (24). We keep iterating on the two equations to convergence, step-by-step. We then decrease $\kappa$, using the previous solutions as initial conditions, until we reach the relevant cases of five-year debt, $\kappa = 0.05$, and 10-year...
debt, $\kappa = 0.025$. 

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REFERENCES


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Ou, Sharon, David Chiu, and Albert Metz, 2011, Corporate default and recovery rates, 1920-2010, Moody's Investors Service, Global Corporate Finance.


Table I
Calibration

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

<table>
<thead>
<tr>
<th>Description</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rate of time preference</td>
<td>$\beta$</td>
<td>0.996</td>
</tr>
<tr>
<td>Relative risk aversion</td>
<td>$\gamma$</td>
<td>7.5</td>
</tr>
<tr>
<td>Elasticity of intertemporal substitution</td>
<td>$\psi$</td>
<td>2</td>
</tr>
<tr>
<td>Growth rate of consumption</td>
<td>$g$</td>
<td>0.0036</td>
</tr>
<tr>
<td>Persistence of Markov chain</td>
<td>$\rho$</td>
<td>0.95</td>
</tr>
<tr>
<td>Persistence of idiosyncratic shock</td>
<td>$\rho_z$</td>
<td>0.85</td>
</tr>
<tr>
<td>Volatility of idiosyncratic shock</td>
<td>$\sigma_z$</td>
<td>0.15</td>
</tr>
<tr>
<td>Capital share</td>
<td>$\alpha$</td>
<td>0.65</td>
</tr>
<tr>
<td>Depreciation rate of capital</td>
<td>$\delta$</td>
<td>0.03</td>
</tr>
<tr>
<td>Proportional costs of production</td>
<td>$f$</td>
<td>0.04</td>
</tr>
<tr>
<td>Corporate tax rate</td>
<td>$\tau$</td>
<td>0.14</td>
</tr>
<tr>
<td>Bankruptcy costs</td>
<td>$\xi$</td>
<td>0.2</td>
</tr>
<tr>
<td>Fixed equity issuance costs</td>
<td>$\lambda_0$</td>
<td>0.06</td>
</tr>
<tr>
<td>Proportional equity issuance costs</td>
<td>$\lambda_1$</td>
<td>0.01</td>
</tr>
<tr>
<td>Fixed debt adjustment costs</td>
<td>$\phi_0$</td>
<td>0.006</td>
</tr>
<tr>
<td>Proportional debt adjustment costs</td>
<td>$\phi_1$</td>
<td>0.02</td>
</tr>
<tr>
<td>Inverse debt maturity</td>
<td>$\kappa$</td>
<td>0.05</td>
</tr>
</tbody>
</table>
Table II
Aggregate Moments

This table reports unconditional moments of consumption growth and asset prices of simulated data. The table shows cross-simulation averages of annual consumption growth, its volatility and autocorrelation, average risk-free rate and risk-free rate volatility, average equity and value premium, volatility of the log price-dividend ratio, aggregate stock return volatility, skewness, and kurtosis, and average firm-level stock return volatility. All moments are annualized. Consumption, risk-free rate, equity premium, and price-dividend ratio data are from Bansal, Kiku, and Yaron (2012). Aggregate stock return volatility, skewness, and kurtosis are based on the CRSP value-weighted index, the value premium is based on the Fama-French (1993) HML factor, and average stock return volatility is based on quarterly CRSP data for the years 1984 to 2011.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average consumption growth</td>
<td>0.019</td>
<td>0.012</td>
</tr>
<tr>
<td>Consumption growth volatility</td>
<td>0.022</td>
<td>0.024</td>
</tr>
<tr>
<td>Autocorr. of consumption growth</td>
<td>0.386</td>
<td>0.398</td>
</tr>
<tr>
<td>Average risk-free rate</td>
<td>0.005</td>
<td>0.003</td>
</tr>
<tr>
<td>Risk-free rate volatility</td>
<td>0.029</td>
<td>0.002</td>
</tr>
<tr>
<td>Average equity premium</td>
<td>0.079</td>
<td>0.072</td>
</tr>
<tr>
<td>Average value premium</td>
<td>0.034</td>
<td>0.040</td>
</tr>
<tr>
<td>Volatility of (log) price-dividend ratio</td>
<td>0.419</td>
<td>0.392</td>
</tr>
<tr>
<td>Aggregate stock return volatility</td>
<td>0.178</td>
<td>0.171</td>
</tr>
<tr>
<td>Aggregate stock return skewness</td>
<td>-0.580</td>
<td>-0.783</td>
</tr>
<tr>
<td>Aggregate stock return kurtosis</td>
<td>3.614</td>
<td>5.142</td>
</tr>
<tr>
<td>Average firm-level stock return volatility</td>
<td>0.339</td>
<td>0.306</td>
</tr>
</tbody>
</table>
This table reports unconditional moments of corporate policies generated by the model. The table shows cross-simulation averages of the average quarterly investment-to-asset ratio and its cross-sectional dispersion, the frequency and size of new equity and bond issuances, average market-to-book ratio, average market leverage and its cross-sectional dispersion, and average profitability and its cross-sectional dispersion. We simulate 100 economies for 28 years each consisting of 3,000 firms and the table shows cross-simulation averages. The data are from the quarterly CRSP-Compustat file covering the years 1984 to 2011.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average investment-to-asset ratio</td>
<td>0.028</td>
<td>0.032</td>
</tr>
<tr>
<td>Dispersion of investment-to-asset ratio</td>
<td>0.075</td>
<td>0.104</td>
</tr>
<tr>
<td>Frequency of equity issuances</td>
<td>0.079</td>
<td>0.085</td>
</tr>
<tr>
<td>Average new equity-to-asset ratio</td>
<td>0.122</td>
<td>0.101</td>
</tr>
<tr>
<td>Frequency of bond issuances</td>
<td>0.299</td>
<td>0.216</td>
</tr>
<tr>
<td>Average new bond-to-asset ratio</td>
<td>0.068</td>
<td>0.085</td>
</tr>
<tr>
<td>Average market-to-book ratio</td>
<td>1.407</td>
<td>1.691</td>
</tr>
<tr>
<td>Average profitability</td>
<td>0.019</td>
<td>0.035</td>
</tr>
<tr>
<td>Dispersion in profitability</td>
<td>0.059</td>
<td>0.074</td>
</tr>
<tr>
<td>Average market leverage</td>
<td>0.282</td>
<td>0.286</td>
</tr>
<tr>
<td>Dispersion in market leverage</td>
<td>0.222</td>
<td>0.253</td>
</tr>
</tbody>
</table>
Table IV
Cross-Sectional Leverage Regressions

This table reports pooled panel regressions of market leverage on size ($\log(K)$), market-to-book ($\left(V + PB\right)/K$), profitability ($\Pi/K$), asset volatility, and the aggregate log price-dividend ratio. We simulate 100 economies for 28 years each consisting of 3,000 firms and the table shows cross-simulation averages. The data are from the quarterly CRSP-Compustat file and CMA. The long sample period is from 1984 to 2011 and the short one from 2004 to 2011. $t$-statistics are clustered at the firm level and reported in parentheses.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Long Sample</td>
<td>Short Sample</td>
</tr>
<tr>
<td>Size</td>
<td>0.009</td>
<td>−0.027</td>
</tr>
<tr>
<td></td>
<td>(10.65)</td>
<td>(−4.09)</td>
</tr>
<tr>
<td>Market-to-book</td>
<td>−0.076</td>
<td>−0.136</td>
</tr>
<tr>
<td></td>
<td>(−40.42)</td>
<td>(−9.69)</td>
</tr>
<tr>
<td>Profitability</td>
<td>−0.286</td>
<td>−1.183</td>
</tr>
<tr>
<td></td>
<td>(−15.42)</td>
<td>(−5.32)</td>
</tr>
<tr>
<td>Asset volatility</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price-dividend ratio</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.189</td>
<td>0.387</td>
</tr>
</tbody>
</table>
Table V
Cyclical Firm Behavior over the Business Cycle

This table reports correlation coefficients of corporate policies with aggregate output growth. We simulate 100 economies for 28 years each consisting of 3,000 firms and the table shows cross-simulation averages. Firm-level data are from the quarterly CRSP-Compustat file, real GDP growth is from the Bureau of Economic Analaysis, and the aggregate U.S. corporate default rate is from Standard & Poors. All data cover the years 1984 to 2011.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average investment growth</td>
<td>0.305</td>
<td>0.680</td>
</tr>
<tr>
<td>Average equity issuance</td>
<td>0.173</td>
<td>0.253</td>
</tr>
<tr>
<td>Average debt issuance</td>
<td>0.334</td>
<td>0.415</td>
</tr>
<tr>
<td>Average market leverage</td>
<td>-0.301</td>
<td>-0.634</td>
</tr>
<tr>
<td>Aggregate default rate</td>
<td>-0.553</td>
<td>-0.729</td>
</tr>
</tbody>
</table>

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Table VI
Term Structure of Credit Spreads

In this table, we report average credit spreads, cumulative actual default rates, and average leverage ratios for different debt maturities, sample periods, and model specifications. Panels A, C, and D correspond to the long sample for which we simulate 3,000 firms for 28 years. The short sample (Panel B) mimics the crisis sample (2004 to 2011) for which we simulate 320 firms for eight years. Credit spread data for the long sample are from Huang and Huang (2012) and those for the short sample are from CMA. Historical default rates are taken from Ou, Chiu, and Metz (2011). Model I refers to the benchmark model, Model II features no financial adjustment costs, Model III removes the irreversible investment constraint, and Model IV features neither financial nor real adjustment costs (reversible investment). Model V removes proportional costs of production but retains all other frictions.

<table>
<thead>
<tr>
<th>Moment</th>
<th>Unit</th>
<th>Data</th>
<th>Model I</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
<th>Model V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Long Sample and 5-Year Maturity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>b.p.</td>
<td>103</td>
<td>107</td>
<td>74</td>
<td>59</td>
<td>51</td>
<td>47</td>
</tr>
<tr>
<td>Cum. default rate</td>
<td>%</td>
<td>1.95</td>
<td>2.03</td>
<td>1.82</td>
<td>1.66</td>
<td>1.58</td>
<td>1.34</td>
</tr>
<tr>
<td>Leverage</td>
<td></td>
<td>0.28</td>
<td>0.29</td>
<td>0.33</td>
<td>0.35</td>
<td>0.36</td>
<td>0.38</td>
</tr>
<tr>
<td>Panel B: Short Sample and 5-Year Maturity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>b.p.</td>
<td>160</td>
<td>165</td>
<td>134</td>
<td>116</td>
<td>102</td>
<td>83</td>
</tr>
<tr>
<td>Cum. default rate</td>
<td>%</td>
<td>2.85</td>
<td>4.35</td>
<td>3.27</td>
<td>2.79</td>
<td>2.53</td>
<td>2.38</td>
</tr>
<tr>
<td>Leverage</td>
<td></td>
<td>0.28</td>
<td>0.33</td>
<td>0.36</td>
<td>0.37</td>
<td>0.39</td>
<td>0.41</td>
</tr>
<tr>
<td>Panel C: Long Sample and 1-Year Maturity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>b.p.</td>
<td>45</td>
<td>37</td>
<td>34</td>
<td>27</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>Cum. default rate</td>
<td>%</td>
<td>0.18</td>
<td>0.16</td>
<td>0.13</td>
<td>0.12</td>
<td>0.09</td>
<td>0.06</td>
</tr>
<tr>
<td>Leverage</td>
<td></td>
<td>0.34</td>
<td>0.37</td>
<td>0.39</td>
<td>0.40</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>Panel D: Long Sample and 10-Year Maturity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Credit spread</td>
<td>b.p.</td>
<td>130</td>
<td>126</td>
<td>97</td>
<td>89</td>
<td>77</td>
<td>68</td>
</tr>
<tr>
<td>Cum. default rate</td>
<td>%</td>
<td>4.90</td>
<td>4.42</td>
<td>3.96</td>
<td>3.81</td>
<td>3.53</td>
<td>3.25</td>
</tr>
<tr>
<td>Leverage</td>
<td></td>
<td>0.26</td>
<td>0.30</td>
<td>0.32</td>
<td>0.32</td>
<td>0.32</td>
<td>0.37</td>
</tr>
</tbody>
</table>

50
Table VII
Univariate Sorts of Credit Spreads

This table reports univariate quintile sorts of credit spreads along market leverage, book leverage, market-to-book (Q), and size (market capitalization) in the data (Panel A) and on simulated data (Panel B). The credit spread data cover the period from 2004 to 2011 and contain CDS rates from on average 320 firms in the CMA database. We mimic this episode in our short sample by simulating 320 firms over eight years, repeating the procedure 100 times.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Market Leverage</th>
<th>Book Leverage</th>
<th>Q</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>53</td>
<td>79</td>
<td>315</td>
<td>371</td>
</tr>
<tr>
<td>2</td>
<td>69</td>
<td>96</td>
<td>204</td>
<td>201</td>
</tr>
<tr>
<td>3</td>
<td>98</td>
<td>134</td>
<td>139</td>
<td>114</td>
</tr>
<tr>
<td>4</td>
<td>166</td>
<td>166</td>
<td>90</td>
<td>71</td>
</tr>
<tr>
<td>5</td>
<td>414</td>
<td>324</td>
<td>53</td>
<td>44</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Model – Short Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
</tbody>
</table>
Table VIII
Double Sorts of Credit Spreads

This table reports unconditional double sorts of credit spreads along market-to-book ($Q$) and either book leverage (on the left) or market leverage (on the right) in the data (Panel A) and on simulated data (Panel B). The credit spread data cover the period from 2004 to 2011 and contain CDS rates from on average 320 firms in the CMA database. We mimic this episode in our short sample by simulating 320 firms over eight years, repeating the procedure 100 times.

<table>
<thead>
<tr>
<th>Q</th>
<th>Book Leverage</th>
<th>Market Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low Mid High</td>
<td>Low Mid High Low-High Low-High</td>
</tr>
<tr>
<td>Low</td>
<td>141 223 458 317</td>
<td>101 118 359 259</td>
</tr>
<tr>
<td>Mid</td>
<td>70 100 229 159</td>
<td>68 99 248 180</td>
</tr>
<tr>
<td>High</td>
<td>49 60 94 45</td>
<td>50 87 251 201</td>
</tr>
<tr>
<td>High-Low</td>
<td>92 163 364</td>
<td>51 31 108 152</td>
</tr>
</tbody>
</table>

Panel A: Data

Panel B: Model – Short Sample

<table>
<thead>
<tr>
<th></th>
<th>Book Leverage</th>
<th>Market Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low Mid High</td>
<td>Low Mid High Low-High Low-High</td>
</tr>
<tr>
<td>Low</td>
<td>148 203 296 148</td>
<td>119 176 292 173</td>
</tr>
<tr>
<td>Mid</td>
<td>104 157 225 121</td>
<td>103 151 226 123</td>
</tr>
<tr>
<td>High</td>
<td>78 101 174 96</td>
<td>84 131 203 119</td>
</tr>
<tr>
<td>High-Low</td>
<td>70 102 122</td>
<td>35 45 89 82</td>
</tr>
</tbody>
</table>
Table IX
Cross-Section of Credit Spreads

This table reports pooled panel regressions of credit spreads on firm characteristics in the data and on simulated data from the model. In the data, CDS rates and asset volatility are based on CMA data. Leverage, market-to-book, size, and profitability come from CRSP-Compustat. The aggregate price-dividend ratio is based on the CRSP value-weighted index. The empirical sample covers quarterly data of an average 320 firms between 2004 and 2011. We mimic that episode in simulated data in the short sample, simulating 320 firms over eight years, repeating this procedure 100 times. \( t \)-statistics are clustered at the firm level and reported in parentheses.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Data</th>
<th></th>
<th>Model – Short Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Leverage</td>
<td>0.089</td>
<td>0.090</td>
<td>0.088</td>
</tr>
<tr>
<td></td>
<td>(8.68)</td>
<td>(7.09)</td>
<td>(6.86)</td>
</tr>
<tr>
<td>Asset volatility</td>
<td>0.064</td>
<td>0.064</td>
<td>0.060</td>
</tr>
<tr>
<td></td>
<td>(7.73)</td>
<td>(7.07)</td>
<td>(6.72)</td>
</tr>
<tr>
<td>Market-to-book</td>
<td>0.006</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.85)</td>
<td>(4.91)</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>−0.002</td>
<td>−0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−2.18)</td>
<td>(−2.37)</td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>−0.071</td>
<td>−0.069</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−2.28)</td>
<td>(−2.19)</td>
<td></td>
</tr>
<tr>
<td>Price-dividend ratio</td>
<td>−0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−3.73)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.306</td>
<td>0.320</td>
<td>0.322</td>
</tr>
</tbody>
</table>

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### Table X

**Frictions and the Cross-Section of Credit Spreads**

This table reports pooled panel regressions of credit spreads on firm characteristics in simulated data for different specifications of the model. We simulate 3,000 firms over 28 years, repeating the procedure 100 times. Model I refers to the benchmark model, Model II features no financial adjustment costs, Model III removes the irreversible investment constraint, and Model IV features neither financial nor real adjustment costs. Model V removes proportional costs of production but retains all other frictions.

<table>
<thead>
<tr>
<th></th>
<th>Model I</th>
<th>Model II</th>
<th>Model III</th>
<th>Model IV</th>
<th>Model V</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>0.124</td>
<td>0.106</td>
<td>0.121</td>
<td>0.129</td>
<td>0.113</td>
</tr>
<tr>
<td>Asset volatility</td>
<td>0.095</td>
<td>0.084</td>
<td>0.081</td>
<td>0.076</td>
<td>0.088</td>
</tr>
<tr>
<td>Market-to-book</td>
<td>0.041</td>
<td>0.038</td>
<td>0.032</td>
<td>0.031</td>
<td>0.034</td>
</tr>
<tr>
<td>Size</td>
<td>-0.032</td>
<td>-0.26</td>
<td>-0.27</td>
<td>-0.24</td>
<td>-0.031</td>
</tr>
<tr>
<td>Price-dividend ratio</td>
<td>-0.014</td>
<td>-0.016</td>
<td>-0.016</td>
<td>-0.015</td>
<td>-0.014</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.521</td>
<td>0.604</td>
<td>0.562</td>
<td>0.611</td>
<td>0.581</td>
</tr>
</tbody>
</table>
Table XI
Risk Premia in Credit Spreads

This table reports average credit spreads, annual default rates, credit risk premia, and stock returns for univariate portfolio sorts along market-to-book (Panel A) and size (Panel B). The credit spread data cover the period from 2004 to 2011 and contain CDS rates from on average 320 firms in the CMA database. We mimic this episode in our short sample by simulating 320 firms over eight years, repeating the procedure 100 times.

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Data</th>
<th>Credit Spread</th>
<th>Credit Spread</th>
<th>Default Rate</th>
<th>Credit Risk Premium</th>
<th>Stock Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Market-to-Book Sort</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (Low)</td>
<td>315</td>
<td>276</td>
<td>2.05%</td>
<td>183</td>
<td>9.0%</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>204</td>
<td>208</td>
<td>1.22%</td>
<td>141</td>
<td>7.7%</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>139</td>
<td>143</td>
<td>0.59%</td>
<td>107</td>
<td>6.5%</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>90</td>
<td>114</td>
<td>0.35%</td>
<td>89</td>
<td>5.6%</td>
<td></td>
</tr>
<tr>
<td>5 (High)</td>
<td>53</td>
<td>82</td>
<td>0.14%</td>
<td>69</td>
<td>4.7%</td>
<td></td>
</tr>
</tbody>
</table>

| **Panel B: Size Sort** | | | | | | |
| 1 (Small) | 371 | 286 | 1.85% | 156 | 8.6% | |
| 2         | 201 | 216 | 1.28% | 139 | 7.5% | |
| 3         | 114 | 145 | 0.73% | 108 | 6.5% | |
| 4         | 71  | 103 | 0.38% | 85  | 5.4% | |
| 5 (Large) | 44  | 76  | 0.11% | 71  | 4.9% | |

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This table reports average stock returns of univariate portfolio sorts based on credit spreads (CS) in Panel A and of unconditional double sorts based on credit spreads and expected actual default rates in Panel B. We simulate 3,000 firms (after dropping the first 200 observations) over 28 years, repeating the procedure 100 times, mimicking the long CRSP-Compustat sample.

<table>
<thead>
<tr>
<th>Panel A: Univariate Sort</th>
<th>Panel B: Double Sort</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Spread</td>
<td>Default Rate</td>
</tr>
<tr>
<td>Low</td>
<td>CS</td>
</tr>
<tr>
<td>5.4%</td>
<td>4.1%</td>
</tr>
<tr>
<td>6.7%</td>
<td>6.5%</td>
</tr>
<tr>
<td>7.3%</td>
<td></td>
</tr>
<tr>
<td>8.1%</td>
<td>8.3%</td>
</tr>
<tr>
<td>High</td>
<td>8.9%</td>
</tr>
</tbody>
</table>