Firm policies and the cross-section of CDS spreads

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Abstract

We study the relation between Credit Default Swaps (CDS) spreads and corporate policies in the context of a structural model of firm’s default that accounts for firm heterogeneity, and real and financial frictions. First, we estimate and test the model using simulated method of moments. We find that the model cannot be rejected by the data and successfully matches the cross section of empirically observed CDS spreads, while addressing the credit spread puzzle. Second, we study how CDS spreads are related to observable characteristics of the firms in the simulated economy and in the observed data. We find that, controlling for financial leverage, CDS spreads are positively related to operating leverage, and negatively related to growth opportunities. Consistent with the idea that growth options reduce the credit riskiness of firms, we find that investments are negatively related to changes in CDS spreads.

JEL Classifications: G12, G32

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1 Introduction

Leverage is the main determinant of credit spreads. However, firms with similar leverage might have very different credit spreads. In this paper, we investigate these two empirical regularities by juxtaposing a sample of empirically observed non-financial firms to a simulated economy generated by a dynamic model of corporate decisions.

We develop a simple structural model of credit risk, in which heterogeneous firms react to exogenous productivity shocks by making investment and financing decisions, subject to a number of frictions. The model therefore encompasses both a dynamic model of investments similar to Zhang (2005) and a dynamic model of capital structure similar to Fischer, Heinkel, and Zechner (1989). Credit risk arises because of the uncertainty that the shareholders will be willing to meet their obligations. Default is therefore an endogenous event in the model. Given the optimal default policy and an exogenously specified pricing kernel, we obtain the price (i.e., spread) of a five year credit default swap (CDS).\(^1\)

We set to investigate the relationship between leverage and credit spreads by estimating the parameters of the model by simulated method of moments (SMM). We specify two sets of moment conditions: first, we ask the model to match the unconditional average book leverage, the unconditional one-year default frequency, and the unconditional average senior secured five year CDS spread. Second, we ask the model to match the cross-sectional distribution of credit spreads, represented by the average CDS spreads of ten decile portfolios obtained by sorting firms based on their book leverage. The estimation exercise is quite successful: first, the model cannot be rejected by the data. Second, the estimation is generally able to reconcile the credit spread “puzzle” of Huang and Huang (2003): the model generates an average credit spread very close to the one that is empirically observed, while at the same time requiring average leverage and default frequency that are also close to the empirical counterparts. Third, the average cross-sectional pricing error is very small (at 6.4 basis points). Moreover the model can reproduce accurately the average CDS of all leverage portfolio, despite the fact that, in the data, the relation between leverage and credit spread is non linear (convex).

\(^1\)While the functional form of the pricing kernel is exogenously specified, we estimate the parameters by matching some aggregate moment conditions: the average and standard deviation of the aggregate Sharpe ratio, the average, standard deviation, and first difference autocorrelation of the one year real risk free rate (i.e., one year constant maturity Treasury rate). The functional form of the pricing kernel allows for countercyclical risk premia. Countercyclical risk premia have been found to be an essential feature of a successful pricing kernel in several studies of credit spreads and equity returns. For example, Zhang (2005), Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), Gomes and Schmid (2010), and Chen (2010).
The estimation exercised described above outlines the importance of leverage in explaining the cross-sectional distribution of credit spreads.²

The empirical evidence however suggests that a large part of the variability in credit spreads is due to factors other than leverage. In other words, firms with similar leverage might have very different credit spreads. For example, considering the ten leverage portfolios that we have used in the SMM estimation, we note that the within portfolio variation of CDS spreads, measured in standard deviations, has roughly the same magnitude as the average portfolio CDS spread, in any given year and for any of the ten portfolios. In summary, leverage is not enough to describe credit spreads. Other economic forces are at work.

Therefore, we set to explore how credit spreads are related to mechanisms, different from leverage, that affect the credit riskiness of a firm. Since our model allows for endogenous dynamics of the capital stock, which determines the production capacity of the firm, we concentrate on the firm’s actual production capacity and cost structure (operating leverage), on the prospects for the future production capacity (growth options) and on the realization of these prospects (investments).

The past, current, and future investment choices are expected to impact credit risk because of two key aspects of the model. First, the exogenous productivity shocks that affect the firms are persistent and exhibit mean-reversion. This generates persistence and mean-reversion in the firm’s profitability. Second, adjustments to both debt and capital stock are subject to frictions. On the one hand, because firms face transaction costs when issuing or retiring securities, adjustments to the debt–equity mix are not perfectly correlated with changes in cash flow risk, as for example in Fischer, Heinkel, and Zechner (1989), and Strebulaev (2007). On the other hand, adjustments to the capital stock are also costly, as for example in Hennessy and Whited (2005) and Zhang (2005). In good states of the world, the option to grow is valuable to bondholders as it is indicative of future profitability. At the same time, because the cost of reducing the capital stock is higher than the cost of expanding, having not realized the option to grow is valuable to bondholders in bad states of the economy, as it spares the possible large adjustment cost related to the need to restructure the firm. Thus firms might have different credit spreads even while having the same leverage.

In this sense, we expect, and find, a positive relation between credit spreads and the

²In the model this is true whether or not the firm is at the refinancing point. If the firm is at the refinancing point and issues new debt, then the leverage decision reflects the cost of debt. Therefore, credit risk and leverage are simultaneously determined as a function of the same factors and their relationship is stronger. If the firm is not at the refinancing point, the relationship is positive, but weaker, as the leverage is not a function of the same factors determining credit risk. [Alessio→Andrea:] what are those other factors?
current production capacity and costs structure, as measured by the firm’s operating leverage, after controlling for financial leverage. High operating leverage, due to the predominance of fixed costs and other overheads on variable costs, makes firms particularly inflexible in bad states of the economy. Therefore, firms with high operating leverage have high downside cash flow risk, and consequently higher probability of not meeting their debt obligations.

We expect, and find, a negative relationship between credit spreads and growth options, after controlling for leverage. Large growth options, because of the persistence in the profitability process, are indicative of future expected profitability and of the possibility to expand the firm, which in turn are positively related to the future ability of the firm to repay current debt. As the relationship between leverage and credit spreads is non-linear, the relation between growth options and credit spreads is also stronger (more negative) for firms with high leverage.

Finally we expect, and find, a negative relationship between investments and changes in credit spreads. As the growth options are realized through an expansion of the capital stock, the position of debt holders is improved as a consequence of the increase in the collateral value of the debt. Similarly, a contraction of the firm decreases the credit standing of the firm because of the decrease in the collateral, and because of the disinvestment cost that the firm has to absorb. Moreover, because the asset adjustment costs are asymmetric, the amount by which disinvestments increase credit spreads is much larger than the amount by which investments decrease credit spreads.

Our paper complements recent contributions in the credit risk literature in several ways. Huang and Huang (2003) show that traditional structural models of credit risk, similar to Merton (1974) and Leland (1994), are not able to solve the “credit spread puzzle” — Such models, when endowed with leverage ratios and default probabilities close to those empirically observed, cannot generate realistic credit spreads. Chen, Collin-Dufresne, and Goldstein (2009) propose an extension of the traditional Merton (1974) framework by introducing habit formation into a pricing kernel that provides counter-cyclical risk premia. This innovation allows the standard Merton model, in which the capital structure is static and there is no investment, to produce an average credit spread on corporate debt similar to the one empirically observed in the BBB credit class, while matching the average leverage and the average default probability of BBB firms. Bhamra, Kuehn, and Strebulaev (2010) and Chen (2010) extend the above framework of state dependent risk premia to the case in which firms can dynamically adjust their capital structure through issuance of new debt, while the asset follows an exogenous stochastic process. Bhamra, Kuehn, and Strebulaev (2010) solve the credit spread puzzle by imposing an initial cross-sectional distribution of leverage (equal to
the one that is empirically observed), and by taking advantage of the non-linear relationship between leverage and credit spreads. Chen (2010) show the importance of considering pro-cyclical recovery rates. Relative to these papers, we concentrate our attention on the cash flow generating process, rather than on the discount factor; we allow firms to follow an endogenous dynamic investment strategy; and we do not require any particular starting point of the cross-sectional distribution of leverage, but instead endogenously obtain a realistic distribution.

Two very recent papers, by Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2011), also aim to solve the credit spread puzzle by allowing the firm to dynamically adjust the asset in place. In particular, Arnold, Wagner, and Westermann (2012) model a firm that can exercise an option to expand, while hypothesizing that capital structure is static, although optimally decided at the beginning of the life of the company. Kuehn and Schmid (2011) model a firm that can simultaneously adjust its capital structure and the production capacity in response to fluctuations to both idiosyncratic and systematic shocks. One main difference between Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2011) is that in the first the actual cross-section of firms is used as a starting point for the simulated sample, while in Kuehn and Schmid (2011) the cross section of market leverage and asset value is endogenously generated. Our model shares many features with the one proposed by Kuehn and Schmid (2011). Differently from them we make use of a very simple pricing kernel that allows us to estimate all the parameters of the model. Differently from Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2011), we estimate the parameters of our model by simulated method of moments and use data on an economically important panel of firms. A further advantage of our approach is that the estimation procedure also allows us to concentrate on cross-sectional pricing relationships, as opposed to focusing on solving the credit spread puzzle.

The paper has the following structure. In Section 2 we introduce the model. In Section 3 we discuss the data. Section 4 describes the model estimation procedure. In Section 5 we study the relationship between credit spreads and firm policies. Our concluding remarks are presented in Section 6.

2 The Model

We propose a partial equilibrium dynamic model of corporate decisions that is characterized by firm heterogeneity and endogenous default. The model is therefore similar, in spirit, to

In what follows, we first characterize an economy composed by heterogenous forms in which the preferences of risk averse investors are summarized by an exogenously specified stochastic discount factor. Second, we describe the firm’s decisions. We model is solved using standard dynamic programming techniques and, when possible, we refer to the terminology, notation, and results contained in Stokey and Lucas (1989).

2.1 The Economy

Information is revealed and decisions are made at a set of discrete dates \( \{0, 1, \ldots, t, \ldots\} \). The time horizon is infinite. The economy is composed by a utility maximizing representative agent and a fixed number of heterogenous firms that produce the same good. Firms make dynamic investment and financing decisions, and can default on their debt obligations. Defaulted firms are restructured and then continue operations, so as to guarantee a constant number of firms in the economy. The agent consumes the dividends paid by the firms and saves by investing in the financial market. We do not derive the industry equilibrium, but instead close the economy by choosing an exogenously specified stochastic discount factor.

There are two sources of risk that capture variation in the firm’s productivity. The first, \( z_j \), is of idiosyncratic nature and captures variations in productivity caused by firms’ specific events. The sub-script \( j \) denotes that the risk is unique to firm \( j \). Idiosyncratic shocks are independent across firms, and have a common transition function \( Q_z(z'_j \mid z_j) \). \( z_j \) denotes the current (or time–\( t \)) value of the variable, and \( z'_j \) denotes the next period (or time–\( (t+1) \)) value.

The second source of risk, \( x \), is of aggregate nature and captures variations in productivity caused by macroeconomics events. The aggregate risk is independent of the idiosyncratic shocks and has transition function \( Q_x(x' \mid x) \).

\( Q_z \) and \( Q_x \) are stationary and monotone Markov transition functions that satisfy the Feller property. \( z \) and \( x \) have compact support. For convenience of exposition, we define the state variable \( s = (x, z) \), whose transition function, \( Q(s' \mid s) \), is defined as the product of \( Q_x \) and \( Q_z \). Moreover, as there is no risk of confusion, we drop the index \( j \) in the rest of the section.
2.2 Firm Policies

We assume that firm’s decisions are made to maximize shareholders’ value. An intuitive description of the chronology of the firm’s decision problem is presented in Figure 1. At $t$ the two shocks $s = (x, z)$ are realized, and the firm cash flow is determined based on current capital stock, $k$, and debt, $b$. Immediately after that, the firm simultaneously chooses the new set of capital, $k'$, and debt, $b'$ for the period $[t, t+1]$. This decision determines $d$, the residual cash flow to shareholders, which can be positive (a dividend) or negative (an injection of new equity capital).

At $t$, the cash flow from operations (EBITDA) depends on the idiosyncratic and aggregate shocks, and on the current level of asset in place, $k > 0$:

$$\pi = \pi(x, z, k) = e^{x+z}k^\alpha - fk,$$

where $\alpha < 1$ models decreasing returns to scale and $f \geq 0$ is a fixed cost parameter that summarizes all operating expenses excluding interest on debt.\(^3\)

The capital stock of the firm might change over time. The asset depreciates both economically and for accounting purposes at a constant rate $\delta > 0$. After observing the realization of the shocks at time $t$, the firm chooses the new production capacity $k'$, which will be in operation during the period $[t, t+1]$. The firm can either increase or decrease the production capacity, and the net investment equals to $I = k' - k(1 - \delta)$. Similar to Abel and Eberly (1994) and many others after them, we assume that the change in capital entails an asymmetric and quadratic cost

$$h(I, k) = (\Lambda_1 \cdot 1_{\{I>0\}} + \Lambda_2 \cdot 1_{\{I<0\}}) \frac{I^2}{k},$$

where $0 < \Lambda_1 < \Lambda_2$ model costly reversibility, and $1_{\{\cdot\}}$ is the indicator function. For convenience of estimation and economic interpretation we reformulate the two parameters cost reversibility parameters in the following way: $\Lambda_1 = \lambda_1/\delta$ and $\Lambda_2 = \lambda_2/\delta$. We will report the estimates of $\lambda_1$ and $\lambda_2$. The economic interpretation of $\lambda$ is straightforward. Take for example an investment equal to $I = \delta k$; the cost of that investment will equal $h(I, k) = \lambda_1 I$.

The debt level might also change over time. At any date, the firm can issue a one-period zero-coupon default-able bond. As is shown in Figure 1, at time $t$ the firm chooses the nominal value of the debt contract $b'$ that will be repaid at $t + 1$. The market value

\(^3\)This is similar to what is assumed by Carlson, Fisher, and Giammarino (2004), Cooper (2006), and Kuehn and Schmid (2011).
of such bond is denoted as $D(s, p, p')$, and it depends on the current state $(s, p)$ and on the choices of the debt and the capital stock, $p'$, that are made after observing the shocks.

Changing the debt level entails a direct adjustment cost, $q(b, b') = \theta |b' - b|$, where $\theta \geq 0$. The issuance decision is contemporaneous to repayment of the nominal value of old debt $b$. Overall, the debt decision generates a net cash flow equal to $D(s, p, p') - b - q(b, b')$.

We assume a linear corporate tax function with marginal tax rate $\tau$. The tax code allows deduction of the depreciation of the asset in place, $\delta k$, and of the interest expenses from the taxable income. Deduction of the interest at maturity of the bond would entail keeping track of the value of the debt at issuance, therefore increasing the number of state variables. To keep the problem numerically tractable, we assume that the expected present value of the interest payment $b' - D(s, p, p')$, denoted as $PI(s, p, p')$, can be expensed when the new debt is issued at time $t$. In case of constant corporate tax, and assuming knowledge of the correct conditional default probability, this is equivalent to the standard case of deduction at $t + 1$. The after–tax cash flow from operations plus the net proceeds from the debt decision is

$$v = v(s, p, p') = (1 - \tau) \pi + \tau \delta k + \tau PI(s, p, p') + D(s, p, p') - q(b, b') - b.$$  \hspace{1cm} (1)

We incorporate insolvency on a cash flow basis as an additional element to standard trade–off costs that are already present in our model. The firm is insolvent on a cash flow basis, $v < 0$, if the after–tax cash flow from operations plus the proceeds from the new debt issuance is lower than the value of the debt that is due. In this case, if the default option is not exercised by shareholders, the company must raise enough new equity capital to cover the cash shortfall and pays a proportional transaction cost $\xi \geq 0$. In other words, to raise capital for $v < 0$, the firm pays a cost $v\xi$. The rationale for modeling cash flow illiquidity stems from the fact there are other financial penalties associated with high leverage (for example, the loss of intangible assets and the disruption of operations) which are paid by shareholders and are hard to measure. These costs are included in our framework in a reduced form by assuming that, in case of financial distress, the firm receives only a portion

\footnote{Notably, this cost is defined neither as a proportion of the repurchased debt nor of the newly issued debt, as it is for instance in Fischer, Heinkel, and Zechner (1989), Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010). The role of this cost in the model is to make the debt level persistent, thus generating an interesting cross–section of leverage in our economy.}

\footnote{For simplicity, we do not model personal taxes. Therefore, the tax disadvantage derived from personal taxation of dividends and capital gains and of coupon payments should be properly considered when the estimate of $\tau$ is analyzed.}

\footnote{The firm is allowed to deduct interest when solvent. In case of insolvency, both the principal and the interest are forgiven by the debt holders in exchange of the ownership of the firm and the interest payment cannot be deducted.}
of the capital that is injected by the shareholders.

The equity payout is therefore equal to

\[ w = w(s, p, p') = [v(1 + \xi \cdot 1_{w<0})] - [I + h(I, k)] \]

where the terms in the first square bracket represent the after-tax cash flow from operations, inclusive of the distress costs if the firm is insolvent on a cash flow basis, and the terms in the second square bracket represent the cash flow from investment or disinvestment. Finally, the distribution to shareholders at \( t \) is equal to

\[ d = d(s, p, p') = w(1 + \varphi \cdot 1_{w<0}). \]  \( (2) \)

If the distribution is positive, the firm pays a dividend to the current shareholders. If the distribution is negative, the firm issues new shares, and \( d \) reflects the amount of equity capital received by the company. In this case, the company incurs a proportional equity issuance cost proportional to \( \varphi \geq 0 \).

### 2.3 The Value of Corporate Securities

Following Berk, Green, and Naik (1999) and more recently Zhang (2005) and Gomes and Schmid (2010), we exogenously define a pricing kernel that depends on the aggregate source of risk, \( x \). The associated one-period stochastic discount factor \( M(s, s') \) defines the risk-adjustment corresponding to a transition from the current state \( x \) to state \( x' \).

The firm can issue two types of securities, debt and equity, which are both priced under rational expectations in a perfectly efficient market.

In dynamic programming terms, the cum-dividend price of equity, \( S(s, p) \), is equal to the sum of current distribution, \( d \), and the present value of the expected future optimal distributions, which is equal to the next period price \( S(s', p') \). Since this sum can be negative, a limited liability provision is also included, in which case the firm is worth zero to the shareholders:

\[ S(s, p) = \max \left\{ 0, \max_{p'} \{d(s, p, p') + \mathbb{E}_s [M(s, s')S(s', p')]\} \right\}. \]  \( (3) \)

The value function, \( S \), is the solution of the functional equation (3). The ensuing stationary optimal policy is defined as follows. The event of default is captured by the
indicator function $\omega = \omega(s, p)$. If currently there is not default, the optimal investment and financing decision is $F(s, p) = (k^*, b^*)$.

We now turn to the evaluation of the debt contract. The payoff to debt holders at the end of next period depends on the currently decided asset and debt, $p' = (k', b')$, the new realization of the shocks $s'$, and on whether the firm is solvent, $\omega' = 0$, or in default, $\omega' = 1$, where $\omega' = \omega(s', p')$.

$$u(s', p', \omega') = b'(1 - \omega') + [\pi' + \tau\delta k' + k'(1 - \delta)] \omega'(1 - \eta). \quad (4)$$

The first term on the right-hand side is the payoff to debt holders in case the firm is solvent. The second term represents the payoff in case of default. In this instance, similarly to Hennessy and Whited (2007), the bondholders receive the sum of the cash flow from operations, $\pi' = \pi(s', p')$, the depreciated book value of the asset, and the tax shield from depreciation, all net of a proportional bankruptcy cost $\eta$. Hence, the current value of the debt, at the time it is issued, equals

$$D(s, p, p') = \mathbb{E}_s \left[ M(s, s')u(s', p', \omega') \right]. \quad (5)$$

One final item that needs to be evaluated is the expected present value of the interest payment, $PI(s, p, p')$, which enters the determination of the taxable income in Equation (1),

$$PI(s, p, p') = [b' - D(s, p, p')] \mathbb{E}_s [M(s, s')(1 - \omega')] \quad (6)$$

Because the interest is deductible only if the firm is not in default, the value in expectation is the conditional probability of survival.

In summary, the model is solved by simultaneously finding the optimal value of $S$, $D$ and $PI$. This is done by numerically solving the fixed point of the Bellman operator in equation (3) subject to the constraints in equations (5) and (6). We describe the numerical approach in Appendix A.

### 2.4 Credit Default Swap Spread

A credit default swap (CDS) is a contract whereby the protection seller pays, at default of a given name, an amount equivalent to the protection buyer’s loss given default. The payment is a proportion of the par value of the obligation. In exchange, the buyer periodical pays
to the seller a sequence of premium payments in arrears until the natural maturity of the contract or until the reference name defaults, whichever happens sooner. At the inception of the contract, the premium (i.e., CDS spread) is determined so that the sum of the expected payments from the protection buyer equals the expected payment from the protection seller.

Let us consider a credit default swap agreement with maturity equal to \( T \) periods. The reference entity is the issuer of an obligation with par value of one unit of capital that can default only at the end of each period. For notational simplicity, in this section, we revert to time subscripts: so that \( s_t = s \) and \( s_{t+1} = s' \). Let \( \mathcal{H}(s_t, s_{t+1}) \) be the price of a contingent claim that pays $1 if state \( s_{t+1} \) occurs and the current state is \( s_t \):

\[
\mathcal{H}(s_t, s_{t+1}) = Q(s_t, s_{t+1})M(s_t, s_{t+1})
\]

Let us now define the price of another contingent claim that pays $1 only if the reference entity defaults for the first time on the obligation \( n \) periods from now as

\[
P_n(s, p, p') = \mathbb{E}_{s_t} \left[ \mathcal{H}(s_{t+n-1}, s_{t+n})\omega(s_{t+n}, p_{t+1}) \prod_{j=1}^{n-1} \mathcal{H}(s_{t+j-1}, s_{t+j})(1 - \omega(s_{t+j}, p_{t+1})) \right]
\]

and the price of a contingent claim that pays $1 if the reference entity does not default within the first \( n \) periods as

\[
S_n(s, p, p') = \mathbb{E}_{s_t} \left[ \prod_{j=1}^{n} \mathcal{H}(s_{t+j-1}, s_{t+j})(1 - \omega(s_{t+j}, p_{t+1})) \right]
\]

Note that, in the above definitions, the firm’s policy, \( p' = p_{t+1} \), does not change from one period to the other; the only part evolving through time is the exogenous state.

Finally, the CDS spread is

\[
cds(s, p, p') = (1 - R)\frac{\sum_{n=1}^{T} P_n(s, p, p')}{\sum_{n=1}^{T} (P_n(s, p, p') + S_n(s, p, p'))} \tag{7}
\]

where \( R \) is the recovery on the face value of a unit bond.
3 Data

The data used in the model estimation and in the rest of the analysis is assembled from different datasets. The data used to estimate the parameters of the stochastic discount factor model is obtained from the Federal Reserve Economic Data (FRED) Saint Louis and from Ken French’s website. In particular we obtain the one year constant maturity Treasury rate and the consumer price index for all urban consumers from FRED. We obtain the returns on a value-weighted market portfolio from Ken French. Availability of one year constant maturity rate limits the sample to the years between 1953 and 2010.

Accounting and financial information at the firm level is obtained from the merged CRSP-COMPUSTAT files. Default events are instead collected by merging several sources: Moody’s KMV, Bloomberg, Standard and Poor’s, and FISD Mergent. These events include Chapter 7 and Chapter 11 filings, missed payments of interest and principal, and are related to both bank and publicly held debt.

Finally, daily time series of senior CDS spreads with a 5 year tenor are obtained from Bloomberg for the period from January 2002 throughout December 2010. In order to get spreads that are representative of the firm’s condition at the end of the fiscal year, we compute the average of the daily mid-point quotes over the last two months of the fiscal cycle.

In order to eliminate concerns about liquidity, we focus on firms that belong to the S&P 500 index at any point in time and that have CDS contracts with a tenor of 5 years trading on their debt. Additionally, we eliminate from the sample utilities and firms in the financial sector. This reduces the size of our sample to 276 unique firms and a total of 2007 firm/year observations.

4 Model Estimation

We estimate the parameters of the model by simulated method of moments (SMM) in two separate rounds. Details about the SMM procedure are given in Appendix C.

We specify the stochastic process of the underlying uncertainty as follows. We assume that $z$ follows an auto-regressive process of first order

$$z' = (1 - \rho_z)z + \rho_z z' + \sigma_z \epsilon'_z. \quad (8)$$
The second source of risk, $x$, also follows an auto-regressive process:

$$x' = (1 - \rho_x)\overline{x} + \rho_x x + \sigma_x \varepsilon_x'. \quad (9)$$

In the above equations, for $i = x, z$, $|\rho_i| < 1$ and $\varepsilon_i$ are i.i.d. and obtained from a truncated standard normal distribution, so that the actual support is compact around the unconditional average. We assume that $\varepsilon_z$ are uncorrelated across firms and time and are also uncorrelated with the aggregate shock, $\varepsilon_x$. We assume that the parameters $\rho_z$, $\sigma_z$, and $\overline{z}$ are the same for all the firms in the economy. $\overline{z}$ and $\overline{x}$ denote the long term mean of idiosyncratic risk and of macroeconomic risk, respectively, $(1 - \rho_i)$ is the speed of mean reversion and $\sigma_i$ is the conditional standard deviation. With this specification, the transition function $Q$ satisfies all the assumptions required for the existence of the value function.

Finally, we specify the SDF as

$$M(s, s') = \beta e^{g(x)(x'-x)}, \quad (10)$$

where the state-dependent coefficient of risk-aversion is defined as $g(x) = \gamma_1 + \gamma_2(x - \overline{x})$, with $0 < \beta < 1$, $\gamma_1 > 0$ and $\gamma_2 < 1$.\footnote{Given our assumptions, the yield of a risk–free zero coupon bond is $1/E_s [M(s, s')]$, where $E_s [M(s, s')] = \beta e^{\mu(x) + \sigma(x)^2/2}$, with $\mu(x) = g(x)(1 - \rho_x)(x - \overline{x})$ and $\sigma(x) = g(x)\sigma_x$.}

We separate the parameters that affect the SDF and the aggregate source of risk, from the parameters that govern the idiosyncratic source of risk and the trade-offs within the firm. We are going to refer to the first exercise as the SDF model estimation, and to the second as the firm model estimation. While it would appear obvious, a simultaneous estimation of all the parameters is not optimal. Risk premia most likely respond to long-term dynamics and therefore require long time series of aggregated data to be properly calibrated. Conversely, our panel of firms covers a relatively short span of time.

### 4.1 SDF Model Estimation

There are five parameters that affect the dynamic and the pricing of the aggregate source of risk: the autocorrelation and conditional standard deviation of the aggregate state variable $x$ ($\rho_x$ and $\sigma_x$), and the three parameters that govern the stochastic discount factor ($\beta$, $\gamma_1$ and $\gamma_2$).

We select five moments conditions that can be derived based on the functional form of the
SDF and that can be reasonably estimated from real data: the mean and standard deviation of the market portfolio Sharpe Ratio,\textsuperscript{8} the mean and standard deviation of the real one–year constant–maturity Treasury rate, as well as the autocorrelation of one year changes in the Treasury rate.

We present the results of the estimation in Table 1. In panel A, we report the estimated parameters with their respective standard errors. The systematic productivity shock parameters, $\rho_x$ and $\sigma_x$, at 0.873 and 0.010 are in line with values that have been reported in the literature. For example, using a completely different sample and estimation procedure, Cooley and Prescott (1995) find estimates equal to 0.860 and 0.014, respectively. Although similarly in line with numbers that have appeared in the literature, the estimates of the parameters of the discount factor are more difficult to interpret. A better description of the properties of the discount factor may be obtained by comparing the five moments conditions used to construct the objective function of the SMM. In the left column of Panel B, we report the value of the moment condition computed from the observed empirical sample (Data), while in the right column we report the moment conditions computed from the simulated sample (Model). We note that the model captures very accurately the risk premia in the economy: the observed annual market Sharpe ratio is equal to 0.428 while the corresponding value on the simulated economy is equal to 0.452. Similarly the average one-year real Treasury rate is 1.7% in the real and in the simulated economy. The model also matches almost exactly the other moment conditions.

\subsection*{4.2 Firm Model Estimation}

After estimating the five parameters that describe the aggregate source of risk and the SDF, the model has 13 more parameters. We fix the depreciation rate $\delta$ at 12% to approximate the average monthly investment rate, in line with the choice made by several authors, for example Zhang (2005) and Gomes and Schmid (2010), and estimate all the remaining by SMM.

We set up our estimation to achieve two goals: first, the model should be able to “solve” the credit spread puzzle, and therefore the average book leverage, the average CDS spread, and the average default frequency in the simulated sample should equal the respective quantities in the empirical sample. Second, the model should be able to generate a realistic cross-section of credit spreads. In order to do so, among the moment conditions we include

\textsuperscript{8}The standard deviation of the Sharpe ratio is computed by bootstrapping the empirical sample 1000 times with replacements.
the average CDS spread of ten portfolios obtained by sorting firms according to their book leverage at the end of each fiscal year. Moreover, to force the model to generate an representative cross-section, we add a penalty moment conditions equal to the percentage of simulated periods in which the model is unable to create enough distributions in leverage that the ten portfolios would not be uniquely identified (i.e., more than 10% of the simulated observations have the same book leverage).

In this respect, our estimation is different from many other studies that calibrate their models to match leverage, credit spread and default frequencies of a typical firm (usually, but not exclusively, a BBB one), as for example Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), and Kuehn and Schmid (2011). Our estimation is also different from the calibration of Bhamra, Kuehn, and Strebulaev (2010) and Arnold, Wagner, and Westermann (2012), who impose their simulation to start from very specific points, in order to replicate actual cross-sectional distributions of credit spreads and leverage within selected risk classes (e.g., A, BBB, BB, B). We endogenously obtain realistic distributions of leverage and credit spreads that match those of a sample of real firms, for which we can observe CDS spreads and actual default events.

4.2.1 Parameter Estimates

We present results of the estimation of the firm model in Table 2. In panel A, we report the estimated parameters with their respective standard errors.

The autocorrelation and volatility parameters of the idiosyncratic productivity shock are in order with what one would expect. The idiosyncratic shocks is less persistent, 0.630 vs. 0.873, then the aggregate shock and more volatile, 0.442 versus 0.010. Both parameter estimates are statistically significant.

The estimated corporate tax rate, \(\tau\), (net of the effects of personal taxes on equity and debt income) is 0.117 and not statistically significant. The point estimate, however, is close to the number, 0.132, estimated by Graham (2000), and used also by Chen (2010) in his calibration, but lower than 0.150 as in other related papers, like Bhamra, Kuehn, and Strebulaev (2010).\footnote{The net tax benefit to debt estimated by Graham (2000) is 0.132 and is obtained as a result of the following equation \((1 - \tau_D) - (1 - \tau_C)(1 - \tau_E) = (1 - 0.296) - (1 - 0.350)(1 - 0.120)\), where \(\tau_E\) is the personal tax rate on equity flows, \(\tau_D\) is the personal tax rate on debt flows, and \(\tau_C\) is the corporate tax rate.}

The estimated equity issuance cost, \(\varphi\), is 0.061 and very close to the values reported by Hennessy and Whited (2005) and Altinkilic and Hansen (2000), 0.059 and 0.051, respectively.
It is not statistically significant. The estimated debt adjustment cost parameter, \( \theta \), is 0.086 and not statistically significant. Other authors have modeled debt issuance costs as a proportion of newly issued debt: Chen (2010) uses 0.01, Fischer, Heinkel, and Zechner (1989), and Bhamra, Kuehn, and Strebulaev (2010) use alternatively 0.01 or 0.03. A direct comparison to this other numbers is therefore difficult, and so is an evaluation of the relative cost of issuing equity versus issuing debt.

The estimate for \( \alpha \) is 0.826. In the literature there does not seem to be a very large consensus on what the value should be. For example, Kuehn and Schmid (2011) set \( \alpha \) to 0.65 in a model very similar to ours. However there are large bounds around those figures: estimates for \( \alpha \) vary between 0.30, as in Zhang (2005) to 0.65, as in Gomes and Schmid (2010).\(^{10}\) We obtain an estimate for the fixed cost parameter, \( f \), equal to 0.609. We found only one other paper that uses a fixed cost specification as proportional to the capital stock: Kuehn and Schmid (2011) use a value of 0.02 at quarterly frequency (0.08 at annual frequency). As we will discuss further the fixed cost parameter has a key role in the ability of the model to generate a reasonable cross-sectional distribution of leverage and credit spreads. A number as small as the one used by Kuehn and Schmid (2011) would allow us to match average firm characteristics, as they do, but would not allow us to generate enough dispersion in the cross-section. Intuitively, this is due to the fact that to replicate the cross-sectional characteristic of the data we need a model with very large cash flow volatility. The three parameters most responsible for this are \( \sigma_y \), \( \alpha \) and \( f \). In our estimation, all of them are quite large. In unreported estimation experiments, we fixed either \( \alpha \) and/or \( f \) to the values we found in the literature, and the fitting was extremely poor, especially on the high credit risk classes.

The estimated value of the bankruptcy cost parameter, \( \eta \), is 0.499. Similarly to the production function parameter, there is not a very strong consensus on what this parameter should be. Gomes and Schmid (2010) use 0.750 (although in a specification where the cost is proportional only to the depreciated value of the asset); Hennessy and Whited (2007) estimate the parameter to be 0.104. Glover (2012) estimates default cost parameters at the firm level (using a simpler model) and finds an average value of 0.432, and values that range from 0.189 for lower rated firms to 0.568 for AAA rated companies.

The estimated value of the recovery rate parameter, \( R \), is 0.314. The estimate seems in line with the empirical evidence presented in the literature: Glover (2012) presents an average recovery rate equal to 0.423 based on Moody’s data; Doshi (2012) reports implied values that range from 0.189 for lower rated firms to 0.568 for AAA rated companies.

\(^{10}\)Gomes (2001) sets \( \alpha \) to 0.3, Hennessy and Whited (2005) estimate a value of \( \alpha \) equal to 0.551, while Hennessy and Whited (2007) estimate a value of 0.620.
estimates based on 5-year CDS contracts of 0.338 and 0.143, for senior and subordinated reference obligations, respectively.

A small set of parameters does not have any direct benchmark for comparison: the investment cost parameter, $\lambda_1$, is very close to zero and statistically insignificant. The disinvestment cost parameter, $\lambda_2$, is estimated to be equal to 0.304, meaning that a disinvestment of 1.3 units of capital from a level of capital equal to 10 units, would cost approximately 0.420 (30% of the disinvestment), thus leading to a cash inflow of 0.880. Finally, the distress cost parameter, $\xi$, is estimated at 0.189.

It is worth pointing out that the total cost of financial distress, which plays an important role in our paper, is not simply given by the parameter $\xi$, but it depends on how the firm decides to resolve the cash short-fall. The firm has essentially two choices that are not mutually exclusive: it can sell a portion of the asset in place (thus incurring an adjustment cost), or it can raise equity capital (thus incurring an equity flotation cost).

Let us say that an financial loss of $v < 0$ is realized: if the firm chooses the first option (i.e., liquidate part of the asset) the equity distribution will equal $w = v(1 + \xi) - I - h(I, k)$, so that the total cost of resolving the financial distress equals $|v|\xi + h(I, k)$. If the firm chooses the second option (i.e., raise equity), then the equity distribution becomes $w = v(\xi + \varphi + \xi \varphi) < 0$, and the total cost of resolving the financial distress is $|v|(\xi + \xi \varphi)$.

Finally, the firm might choose to, or might have to, rely on both. In this case, the cost of resolving the financial distress is $|v|(\xi + \varphi + \xi \varphi) + h(I, k)(1 + \varphi) + I \varphi$. In either one of those three cases the cost of financial distress is approximately between 23% and 26% of the actual loss.\footnote{To illustrate how large the impact of financial distress can be, the effect of non-linearity of the adjustment cost with respect to the disinvestment, and the dependence of the current capital stock, assume that a firm has a cash shortfall $v = -0.1$. Let’s assume that the firm may decide one of the four alternative investment policies: $I = 0, -0.05, -0.1, -0.15$.

To begin with, assume the capital stock is low, say $k = 3$. If $I = 0$, then the actual payout will be $d = -0.1$ and the cost $-v(\xi + \varphi + \xi \varphi) = 0.0262$, or about 26% of the cash shortfall. If $I = -0.05$ or $I = -0.1$, the corresponding payouts will be $d = v - I = -0.05$ or 0 and the costs $-v(\xi + \varphi + \xi \varphi) + h(I, k)(1 + \varphi) + I \varphi = 0.0253$ and 0.0290, respectively. Finally, if the firm decides to disinvest more than needed to resolve the financial distress, $I = -0.15$, the dividend would be $d = v - I = 0.05$, with an associated overall cost of $-v \xi + h(I, k) = 0.0379$. While, based on these examples, nothing can be said about the optimality of the four policies, from a cost-minimization perspective the best is to sell asset, $I = -0.05$, while raising also 0.05 of equity capital: this leads to an overall cost of about 25% of the cash shortfall. Thus, the examples show that in the model the trade-off between real and financing frictions can be non-trivial, due to the convexity of the adjustment cost function, $h(I, k)$.

To show how the cost of resolving the financial distress is affected by the current capital stock, consider the same example but for a larger firm, with $k = 8$. While the cost is independent of $k$ if $I = 0$, in the other cases the cost is generally lower than for a smaller firm. Specifically, if $I = -0.05$ or $I = -0.1$, the overall cost $-v(\xi + \varphi + \xi \varphi) + h(I, k)(1 + \varphi) + I \varphi = 0.0239$ and 0.0234, respectively. Finally, if $I = -1.5$, the cost
4.2.2 Model Fit

In panel B of Table 2, we compare the 14 moment conditions used to construct the objective function of the SMM: the average book leverage, the average five-year CDS spread, the annual default frequency, the percentage of years in which the model produces enough cross-sectional dispersion so that we are able to sort simulated observations in ten decile portfolios (i.e., there are not more than 10% of the observations in one year that have the same book leverage). In the left column we report the value of the moment condition computed from the observed empirical sample (Data), while in the right column we report the moment conditions computed from the simulated sample (Model).

Given the estimated parameters, the model is able to generate a 41.9% average book leverage that is very close to the 43.1% observed in the data. At the same time, it produces an average credit spread, 1.3%, and an average one-year default frequency, 0.521%, that are also very close to the respective empirically observed quantities, 1.3% and 0.491%. The model also produces a realistic cross section of leverage ratios almost all the times (99% of valid sorting). The model thus achieves the first goal and is able to explain the credit-spread puzzle.

On the second front, generating a realistic cross–section of CDS spreads, the model is also successful. The absolute mean pricing error of the ten leverage portfolios is equal to 6.4 basis points, while the maximum is 12.1 basis points (the minimum is 0.1), indicating that all portfolios are reasonably priced. Moreover, as we can observe from Figure 2, the model is not only able to generate an upward sloping curve (higher leverage leading to higher CDS spreads) that is in line with the empirical counterpart, but it is also able to replicate the non-linearity between credit spreads and the highest leverage portfolios (i.e., the relation between leverage and credit spreads is overall convex).

Overall, the model cannot be rejected by the data. The test of overidentifying restriction cannot reject the null hypothesis at conventional statistical levels: the Hausman J-statistic is equal to 4.103 with a critical value of 5.991 at the 95th confidence level (and $2 = 14 - 12$ degrees of freedom).

\[ -v \xi + h(I, k) = 0.0260. \] This shows that, in the model, for a larger firm, in case of insolvency on a cash flow basis, it is relatively less expensive to sell assets, at an overall cost of about 23% of the shortfall.

To fully appreciate the impact of distress costs in the model, let reconsider the above example, with $k = 3$, assuming that $\xi = 0$. In this case, holding everything else equal, for $I = 0$ the overall cost is 6.1% of the cash shortfall, for $I = -0.05$ it is 5.3%, for $I = -0.1$ it is 8.9%, and for $I = -0.15$ it is 19%. Therefore, excluding distress costs from the model forces a much higher (and most likely unrealistic) estimates for either $\lambda_2$ or $\varphi$. 

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4.2.3 Alternate Specifications

In this section we discuss the impact of changing some key features of our model. We repeat the estimation exercise while excluding some features of the model. It is important to note that in each of these cases we estimate a model in which firm’s policies and credit spreads are in equilibrium. In particular, removing any feature of the model induces a change in the firm’s optimal policies: this might impact the overall ability of the model to fit the moment conditions, or might change the estimates of the parameters, which can become either statistically insignificant or economically implausible.

We will focus on four key features of the model: the presence of distress costs, $\xi$; the role of fixed costs, $f$; the impact of real adjustment costs, $\lambda_1$ and $\lambda_2$; the role of financing frictions, in the form of equity floatation costs, $\varphi$, and debt adjustment costs, $\theta$. The results of the five estimation exercises are reported in Table 3.

In the first alternate specification, we exclude financial distress costs (and therefore the state of financial distress) by setting $\xi$ equal to zero. The goodness of fit of this model is lower than the base case scenario and the model can now be rejected by the data: this is mainly due to the fact that this specification produces a higher average leverage than the one found in the data or in the base case model, and diminished ability of the model to create cross-sectional heterogeneity. In economic terms, eliminating the financial distress cost channel leads to the amplification of other cost channels: higher taxes (almost double) and higher capital adjustment costs (again almost double the base case parameters). Also this is the only variant of the model in which the debt adjustment costs appear to be statistically significant. The total effect is to increase credit spreads, as well as the default frequency.

The second variation on the model is given by the exclusion of fixed costs from the determination of the firm’s cash flow, i.e., we set $f$ equal to zero. Interestingly the ability of the model to create cross-sectional heterogeneity is directly link to the operating leverage. Without fixed costs, the model is completely unable to create dispersion among firms, a feat that is achieved in less than 8% of the simulated years. Similarly to the previous case, after eliminating one of the principal cost source, the estimation exercise reacts by increasing other costs: taxes, distress costs, and cost of contraction. Notably the estimation also returns a much higher degree of autocorrelation for the idiosyncratic productivity process. In summary, the model is rejected by the data.

In the third specification we suppress the capital adjustment costs, $\lambda_1$ and $\lambda_2$. Note that the expansion costs was not economically or statistically important in the base case scenario, so that the real change here is the elimination of the contraction cost. Regardless,
this changes the ability of the model to fit the data. The model is in fact statistically rejected by the data, and it produces higher leverage, credit spreads and default probabilities. Surprisingly the elimination of the contraction cost does not lead to an increase of the distress cost (on the opposite the parameter is much smaller). Even more surprisingly, this leads the model to produce higher leverage, credit spreads and default frequency.

The fourth and final alternative specification is characterized by the absence of issuance costs, as both the equity floatation cost and the debt adjustment costs parameters are set to zero. Not surprisingly, since those estimates were not statistically significant in the base case scenario, this variant of the model is the one that comes closer to the base case.

What we learn from this exercise is that not all trade-offs are important in terms of their ability to help the model to match the cross-sectional features of the data. Clearly, the operating leverage plays a big role in this type of models. Adjustment costs seems important only when it comes to contraction, while expansion costs do not seem to be that important. Also, equity issuance costs and debt adjustment costs do not appear to be key ingredients of a successful model. On the other hand, some of these features might be more important for a model focused at capturing time-series dynamics (i.e., financial frictions help explain some path dependencies that can be observed in the data).

5 CDS Spreads and Firm Policies

The estimation exercised described in the previous section outlines the importance of leverage in explaining the cross-sectional distribution of credit spreads, as the model does a remarkable job at pricing the ten leverage portfolios. The empirical evidence however suggests that a large part of the variability in credit spreads is due to factors other than leverage. In other words, firms with similar leverage might have very different credit spreads. For example, considering the ten leverage portfolios that we have used in the SMM estimation, we note that the within portfolio variation of CDS spreads, measured in standard deviations, has roughly the same magnitude as the average portfolio CDS spread, in any given year and for any of the ten portfolios. A similar perspective can be gathered by observing that in a linear regression, even controlling for industry and time fixed effects, leverage explains less than 50% of the cross-sectional variation of credit spreads.\textsuperscript{12} In summary, leverage is not enough to describe credit spreads. Other economic forces are at work.

\textsuperscript{12}Notably, this is contemporaneous leverage, which at the firm’s refinancing point is chosen also as a function of the cost of debt and the credit spread.
In this section we explore whether some of the variation in credit spreads that is not
due to variation in leverage is related to other economic mechanisms that affect the credit
riskiness of a firm. Since our model differs from others principally in the fact that we allow for
endogenous dynamics of the capital stock, which determines the production capacity of the
firm, we concentrate on the firm’s actual production capacity and cost structure (operating
leverage), on the prospects for the future production capacity (growth options) and on the
realization of these prospects (investment policy), vis–a–vis the financing policy.

Notably, the relationships that we set to explore have not been used in the model esti-
mation. The following analyses are therefore interesting for two reasons. First, they help
us uncover some of the economic mechanisms that govern the model. Second, the juxtapo-
sition of the simulated world with the empirical data serves as an additional inference on the
ability of the model to capture the fundamental trade-offs that lead firms to make particular
choices and markets to evaluate them.

5.1 Operating leverage and credit spreads

In this section, we examine the relation between credit risk and operating leverage (i.e., the
volatility of cash flow related to the incidence of fixed costs). The operating leverage of the
firm at the end of period \(t-1\) is measured by the ratio of fixed production costs over
EBITDA

\[
OPL(s, p) = \frac{e^{x+z}k^{\alpha} - \pi(s, k)}{\pi(s, k)} = \frac{fk}{\pi(s, k)}.
\]  

The equivalent to equation (11) in the observed data is given by the difference between sales
and EBITDA, over EBITDA.

While we model insolvency both from a value and a cash flow perspective, operating
leverage is an important determinant of credit risk from a cash flow perspective. Everything
else equal, large fixed costs make the firm more likely to be insolvent on a cash flow basis in
a downturn, thus reducing the firm ability to meet the debt obligations.

In Table 4 we report results of panel regressions of 5-year CDS spreads on book leverage
and operating leverage. In the first two columns, labeled Data, we report results obtained
from the empirical sample. In columns (3) and (4), labeled Model, we report results
obtained from the simulated sample. This last set of results is obtained by estimating the
regression parameters for each of the 50 simulated samples. The reported parameters are
then computed by averaging across the 50 estimations. Similarly, the standard error of each
parameter is obtained as the standard deviation of the 50 estimates of the parameter itself.
All regressions include time fixed effects. The regressions based on the *Data* sample also include industry fixed effects, and have standard errors clustered at firm level.

As we can see from columns (1) and (3), controlling for book leverage, operating leverage has a positive and statistically significant coefficient. High fixed costs, and in general a large overhead, increase the likelihood of having insufficient funds to service the debt if a bad scenario occurs. The estimated coefficient on the interaction term between book and operating leverage, columns (2) and (4), is not statistically significant.

A similar perspective can be obtained from independent quartile sorting of CDS spreads by book leverage and operating leverage. In Panel A of Table 5 we report results obtained from the empirically observed data (*Data*), while in Panel B we report results for the simulated sample (*Model*). For all the leverage quartiles, there is a positive relationship between credit spreads and operating leverage. As evidenced in Panel A and consistent with the sign of the interaction variable in the regression model, the relation becomes stronger for higher leverage.

### 5.2 Growth options and credit spreads

In this section, we discuss the relation between credit risk and growth opportunities. In the context of our model, this relation can be easily understood by observing Figure 3. There are two basic mechanisms that generate growth options. The first mechanism can be highlighted by considering, at a particular date, two firms with the same ratio of debt to asset in place (i.e., the same book leverage) and the same capital stock. Let’s assume that the first firm has just observed a positive realization while the second has observed a negative realization of the idiosyncratic shock. The first firm has higher growth options than the second one. Because the shocks are persistent, the option to grow is due to the fact that the firm is on a high trajectory of the firm specific shock, and therefore expects also a positive shock in the next period. If that shock is large enough the firm might decide to invest (this might depend on the aggregate shock).

We illustrate the second mechanism also with an example. We now consider two firms with the same leverage but different levels of capital stock (i.e., different size, as measured by the book value of the assets). Let’s assume that both firms observe a positive idiosyncratic shock. The future prospects of the two firms are not the same. In fact, because the production function exhibits decreasing return to scale, the smaller firm has better future
prospects and hence more growth options.\textsuperscript{13}

In summary, cross-sectional differences in growth options for firms with the same leverage arise because firms have different capital in place and/or because they are on different trajectories of the firm specific shock. Because of that, some firms find themselves in a situation in which they expect to be very profitable in the future.

The relation between credit risk and growth options can now be easily formalized. With one period debt, investments and debt repayment are contextual (i.e., the two decision are simultaneous). Since growth options signal the ability of the firm to make future investments because of the expected future profitability, they also signal the expected ability of the firm to repay current debt. Accordingly, after controlling for book leverage, the relation between credit spread and growth options should be negative.

In Table 6 we present the estimation results of panel regressions of 5-year CDS spreads on book leverage and market–to–book, or Q for short, ratio. In the first two columns, labeled \textit{Data}, we report results obtained from the empirical sample. In columns (3) and (4), labeled \textit{Model}, we report results obtained from the simulated sample. This last set of results is obtained by estimating the regression parameters as we explained previously. All regressions include time fixed effects. The regressions based on the \textit{Data} sample also include industry fixed effects, and have standard errors clustered at firm level.

As we can see from columns (1) and (3), controlling for book leverage, the Q–ratio has a negative and statistically significant coefficient. While the relation between CDS spreads and market–to–book is on average negative, it is not obviously negative for all levels of leverage. We include an interaction term between leverage and market–to–book in columns (2) and (4). The estimated coefficient on the interaction term suggests that the relation is more pronounced for high leverage firms, while it is at best very weak for low leverage firms.

A similar perspective can be obtained from independent quartile sorting of CDS spreads on book leverage and market–to–book. In Panel A of Table 7 we report results obtained from the empirically observed data (\textit{Data}), while in Panel B we report results for the simulated sample (\textit{Model}). The sorting procedure in the case of the simulated sample involves first sorting in each time period of each one of the 50 simulated samples. Next, we average across time. Finally, the results reported are obtained by averaging across the 50 simulated samples. For all the leverage quartiles, there is a negative relationship between credit spreads and market–to–book ratio. As evidenced in Panel A and consistent with the significance of the interaction variable in the regression model, the relation becomes stronger for higher

\textsuperscript{13}This effect is what is reproduced also by Carlson, Fisher, and Giammarino (2004) in their model.
leverage. In Panel B there is a similar pattern, but for the highest leverage quartile of simulated firm.

The model allows us to interpret the negative and statistically significant interaction term between market to book ratio and book leverage in terms of insolvency on a cash flow basis. A high market to book ratio proxies for a high expected future cash flow (or profitability) and this is more beneficial for firms with more debt, in terms of their ability to meet financial obligations. On the contrary, firms that do not have much debt, do not need high future cash flows to meet their obligations.

Notably, the results discussed in this section are apparently in contrast with the predictions of the theoretical models proposed by Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2011). Although the predictions of our model line up with the empirical evidence, some discussion is required.

Therefore, in the rest of this section, we make a few considerations about some of the most troubled economic hinges on which the relation between credit risk and growth options rests. First, we explore two issues that make the relation between credit spreads and market to book ratio difficult to interpret as equivalent to the relationship between growth options and credit risk: we discuss the choice of book and market leverage as the proper control in a regression of credit spreads on growth options. Moreover, we investigate the information content of the market to book ratio as a proxy for growth options, and try to distinguish the value of the options to grow from the value of the assets in place. Second, we borrow from the framework in Arnold, Wagner, and Westermann (2012), and discuss the relative impact of distinct value channels that affect growth options.

5.2.1 Growth options, book and market leverage

The relation between credit spreads and the market to book ratio is affected by the choice of which leverage measure is used in the regression. For example, including (quasi) market leverage instead of book leverage in Table 6 would lead the parameter of the market to book ratio to switch sign (from negative to positive), as for example reported by Kuehn and Schmid (2011).

Both signs are theoretically possible as the following example illustrates. Consider two firms, denoted 1 and 2, with the same book leverage, $b_1'/k_1' = b_2'/k_2'$, and different book to market ratio, $b_1'/k_1' + S_1/k_1' > b_2'/k_2' + S_2/k_2'$. Using the first equality, the second condition can be rewritten $S_1/k_1' > S_2/k_2'$, which suggests that the firm with higher book to market
ratio ratio has relatively higher equity valuation and better prospects. Since those are negatively related to the probability that firm has financial problem, it leads to a negative correlation between credit spreads (risk) and market to book ratio. This is what we find in our analysis.

Consider now two firms with the same quasi-market leverage $b'_1/(b'_1 + S_1) = b'_2/(b'_2 + S_2)$, or after some easy manipulation $S_1/b'_1 = S_2/b'_2$. The two firms have different book to market ratio, $b'_1/k'_1 + S_1/k'_1 > b'_2/k'_2 + S_2/k'_2$, or equivalently $(1 + S_1/b'_1)b'_1/k'_1 > (1 + S_2/b'_2)b'_2/k'_2$. After using the quasi-market leverage equality, the last inequality can be rewritten as $b'_1/k'_1 > b'_2/k'_2$. What we learn is that, fixing the quasi-market leverage, the firm with higher market to book ratio has higher book leverage and therefore higher credit risk. Therefore, controlling for quasi-market leverage, the correlation between credit spreads and market to book ratio should be positive. This is what Kuehn and Schmid (2011) find.

In summary, what we learn is that controlling for market leverage might lead to a problematic interpretation of the sign of the market to book ratio coefficient in a regression of credit spreads.

5.2.2 Market to book ratio, options to grow and asset in place

The relation between credit spreads and market to book ratio is also affected by the fact that the market to book ratio contains information about the firm that is not directly related to growth options. We explore this issue in this section.

In the model, a growth opportunity is the option to build additional production capacity through investments. In order to measure the value created by growth options, we first determine the value of the equity when the firm follows the optimal policy $p^* = (k^*, b^*) = F(s, p)$ subject to the constraint that it cannot increase the production capacity, i.e., $k$. We define $S^{ng}$ (equity with no-growth) as the fixed point of the following functional equation

$$S^{ng}(s, p) = \max \{0, d^{ng} + \mathbb{E}_s [M(s, s')S^{ng}(s', p')]\}, \quad (12)$$

where $p' = (k', b') = (k^*, b^*)$ if $k^* \leq k$, and $(k', b') = (k, b^*)$ if $k^* > k$. Because $S^{ng}$ is obtained from $S$ by imposing a stationary sub-optimal policy, the value of the equity in the case of no-growth, $S^{ng}$, is strictly less than the optimal value of the equity, $S$. The difference between $S$ and $S^{ng}$ has two components: the first originates from the effect of the inability to grow (i.e., the current investment policy) on the dividend, which will be different from the optimal dividend, $d - d^{ng}$. The second component is originates from the effect of
the inability to grow on the continuation value, which in essence is the value of the growth opportunities (i.e., the ability to increase $k$ in the future).

The definition of $S^{ng}$ allows us to decompose the total firm value into three parts: $b' + S = b' + S^{ng} + (S - S^{ng})$: the value of the debt, the present value of the asset in place, $S^{ng}$, and the present value of growth opportunities, $(S - S^{ng})$.

Thus, the market to book value can also be decomposed into three parts:

$$Q = \frac{(b' + S)}{k'} = \frac{b'}{k'} + \text{PVAP} + \text{PVGO}.$$  \hspace{1cm} (13)

where $b'/k'$ is the book leverage; PVAP is the ratio of the present value of the the asset in place, which includes the option to liquidate part of the capital stock and the option to default, to the book value of asset, $S^{ng}/k'$; PVGO is the ratio of the present value of growth opportunities to the book value of asset, $(S - S^{ng})/k'$.

What we learn form Equation 13 is that the market to book ratio contains information not only about growth options, but also about the firm’s credit riskiness. The decomposition suggests that the use of the market to book ratio as a measure of growth options is feasible only after netting out the effect of book leverage as a proxy for credit risk. However, even after controlling for book leverage, there is still an issue that the negative relation between credit spreads and the market to book ratio could be attributed to the value of the asset in place, rather than to the growth options.

Unfortunately, this particular ambivalence cannot be resolved within the context of the observed data, as it is impossible to exactly disentangle the value of the asset in place from the value of the growth opportunities.\footnote{Arnold, Wagner, and Westermann (2012) and Davidenko and Strebulaev (2007) includes R&D expenditure as control for growth options in an attempt to get around the problem.} We therefore defer to the simulated sample. Table 8 shows the estimation results of panel regressions that include as independent variables the present value of the asset in place, PVAP, and the present value of the growth opportunities, PVGO, as defined above. The results reported in the table, suggest a negative relation of credit spreads with PVAP (column 1), PVGO (column 2), and PVAP and PVGO together (column 3). Interestingly, when all three are included PVAP, PVGO, and market to book ratio (after excluding book leverage) the sign of the coefficient in front of the market to book ratio becomes positive (column 5), confirming that after removing PVAP and PVGO, the ratio contains information related to the credit risk of the firm.
5.2.3 Volatility effect versus value effect

We are going to simplify the terms of the argument for sake of brevity. A much better description of the following reasoning can be found in Arnold, Wagner, and Westermann (2012). The option to grow matters to bond holders only in downturns, because that is when their cash flows are affected by company decisions. In a downturn the cash flow volatility of the firm goes up and that increases the value of the growth option. This is known as volatility effect.

At the same time, a down turn decreases the value of capital (i.e., the value of the underlying). This is going to decrease the value of the option to grow, because new capital in place is less valuable. This is known as value effect.

The sign of the relation between credit spreads and growth options is therefore dictated by which one of these two effects is prevalent. Obviously, anyone of those two effects can become prevalent in any model that contains growth options depending on the model calibration.

Although in our setting, all these effects are not explicit, they are nevertheless at play. So one simple reconciliation of the theoretical result proposed by Arnold, Wagner, and Westermann (2012) and the results reported in Table 6, is that in their model’s calibration the value effect is more prominent, while in the empirical sample that we examine, and consequently in our model’s calibration, the volatility effect is more prominent.

5.3 Path dependences, investments and credit spreads

The model is characterized by path dependencies of the policies. At any period, in fact, the firm’s optimal policies (investment, debt issuance and equity distributions) depend on the asset and debt choices that the firm made in the previous period. Consequently, both the firm’s leverage and the firm’s credit spread exhibit path dependencies.

This particular aspect of model has been neglected in the previous sections. We analyze it here. Path dependency in the policies has two important consequences for our analysis of credit spreads. First current credit spreads should also depend on past choices of debt and capital. Second, changes in credit spreads should be associated with changes in the policies (i.e., changes in capital and changes in debt). We analyze those two possible economic determinants of credit spreads separately.

In Table 9, we report panel regressions of 5-year CDS spreads on current and lagged log
levels of asset size and debt amount. In the left panel, labeled Data, we report results for the observed data. In the right panel we report results based on the simulated economy, Model. The results reported in Columns (2) and (5) show that, after controlling for the expectations of future cash flows through the market to book ratio, credit spreads are negatively correlated with the contemporaneous asset level and positively correlated with the contemporaneous debt level. This is equivalent to what we find in Columns (1) and (4), that the credit spreads (respectively, empirically and in the model) are positively correlated with book leverage.

Absent financing and real frictions, the new level of asset and debt would depend only on the realized shocks. However, because adjustments are costly, the chosen levels of asset and debt depend also on their respective lagged values. In other words, firms with the same current leverage, $b'/k'$, and that are exposed to the same shocks may have different credit spreads according to what their respective previous levels of asset and debt were. Column (3) and (6) of Table 9 show that credit spreads are negatively related to current assets and positively related to lagged assets. Similarly credit spreads are positively related to current debt and negatively related to lagged debt.

In Table 10 we report regression results of changes in CDS spreads in on several firm characteristics. In columns (1) and (3) we consider changes in leverage. As should be expected, changes in leverage and changes in credit spreads are positively related. In column (4) we decompose the changes in leverage between changes in debt and changes in assets. Note that because the adjustment costs to the asset are asymmetric (i.e., it costs more to disinvest than it does to invest) the impact of an asset change on credit spreads is not symmetric. The amount by which disinvestments increase credit spreads is much larger than the amount by which investments decrease credit spreads. The investment and disinvestment coefficients are different also in column (2), confirming that investment adjustment costs are an important determinant of the credit risk of a company.

### 6 Conclusion

We develop a structural model of credit risk that allows for dynamic investment and financing policies, and that features financing and real frictions. Heterogeneity among firms is a central aspect of the model and it enables us to study the cross-sectional relationship between credit risk and the economic forces that drive firms in the economy. The model is structurally estimated to capture the empirical cross–section of credit spread in relation to the leverage.

However, what we learn from our estimation exercise is that current leverage, although
important, is not the only driver of credit risk, as this depends on a number of firm characteristics. Because firms policies are path dependent and because exogenous productivity shocks are persistent, the past and the future also matter: current credit spreads are related to current and past values of the capital stock and the debt, as well as the future economic prospects of the firm (growth options). When the firm realizes the option to grow, by investing in production capacity, its credit standing improves.
Appendix

A  Numerical procedure

The solution to the Bellman equation (3) with the constraints in equations (5) and (6), and the related optimal policy is obtained by discretizing the state space of $s = (x, z)$ and the control variables $p = (k, b)$. Because the stochastic process of systematic risk is quite persistent we discretize the two exogenous processes using the numerical approach proposed by Rouwenhorst (1995). $x$ is discretized with 11 points and $z$ with 11. The discretized set of values for capital stock is $\{k_j = k_u(1 - d)^j \mid j = 1, \ldots, N_k\}$, and the set of discrete debt levels is $\{b_j = j \frac{k_u}{N_k} \mid j = 1, \ldots, N_b\}$ with $N_k = 21 = N_b$. The fixed point of the Bellman equation, $S$, is found using a value function iteration algorithm, and the algorithm is halted when the maximum change of value on $S$ between two iteration is below the tolerance $10^{-5}$.

The simulated economy is composed of 50 different samples, characterized by different histories of the aggregate state variable. Each sample is composed by a panel of 300 independent firms, which are characterized by different histories of the idiosyncratic variable. To make the simulated economy comparable to the observed data, each firm’s history, after the first 20 periods are discarded, is composed by 10 periods. The desired quantities are obtained by applying the optimal policy at each step. If a company defaults at a given step, it is restarted at the steady state for $k$ and $b$ one step later.

B  CDS spread

The CDS spread in equation (7) is calculated within our model as follows.

Defining $\mathcal{H}(s, s') = Q(s, s')M(s, s')$, the product of the transition probability and the stochastic discount factor, and given the state dependent default policy $\omega$, we can define $H_d$, the matrix of prices (using the discretized version of the transition function) of contingent claims that pay one unit if we have a transition from a non–default state to a default state in one period, and $H_{nd}$, the matrix of prices of contingent claim that pay one unit if there is a transition from a non–default state to a non–default state.

Using a matrix notation, we define $P_i = H_{nd}^{i-1}H_dI_d$ and $S_i = H_{nd}^iI_{nd}$, where $I_d$ is a column vector of ones with as many components as the number of default states, and $I_{nd}$ is a column vector of ones with as many components as the number of non–default states. Then, the
credit spread is
\[ cds = (1 - R) \frac{\sum_{i=1}^{T} P_i}{\sum_{i=1}^{T} (P_i + S_i)} \]

C Estimation method

The model is estimated in two steps using the Simulated Method of Moments (SMM) of Gourieroux, Monfort, and Renault (1993) and Gourieroux and Monfort (1996). First we estimate the parameters of the stochastic discount factor by matching some aggregate moment conditions: the average and standard deviation of the aggregate Sharpe ratio, the average, standard deviation, and first difference autocorrelation of the one year real risk free rate (i.e., one year constant maturity Treasury rate). Second, we estimate the parameters of the firm’s model by matching moments constructed on some firm level quantities.

In each step we solve a similar version of the following program

\[ \hat{\theta} = \arg \min_{\theta} \{ G_N(\theta)' W_N G_N(\theta) \}, \tag{14} \]

where

\[ G_N(\theta) = m_N - \frac{1}{J} \sum_{j=1}^{J} \tilde{m}_j(\theta) \]

and \( W_N = [N \text{var}(m_N)]^{-1} \) is the efficient weighting matrix, \( m_N \) are the empirical moments based on \( N \) observations, \( \tilde{m}_j \) are the simulated moments based on \( n \) observations in each sample \( j \). We calculate the efficient matrix \( \text{var}(m_N) \) by bootstrapping, with replacement, the data 5000 times.

Following Pakes and Pollard (1989), standard asymptotic arguments can be applied so that for \( N \to \infty \),

\[ \sqrt{N}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, \Omega), \]

where

\[ \Omega = \left(1 + \frac{1}{J}\right) (\Gamma' \Lambda^{-1} \Gamma)^{-1}, \]

with

\[ \Gamma = \text{plim}_{N \to \infty} \frac{\partial G_N(\theta_0)}{\partial \theta}, \]

and \( \Lambda = N \text{var}(m(\theta_0)) = N \text{var}(\tilde{m}(\theta_0)) \). \( \Gamma \) is computed by numerically differentiating \( G_N(\theta) \) around \( \hat{\theta} \), and \( \Lambda \) is approximated by \( N \text{var}(m_N) \).
Because
\[ \sqrt{N} G_N(\theta_0) \xrightarrow{d} \mathcal{N}\left(0, \left(1 + \frac{1}{J}\right) \Lambda\right) \]
we can compute a test statistic for overidentifying restrictions as
\[ \frac{N J}{1 + J} G_N(\theta_0)' \Lambda^{-1} G_N(\theta_0) \xrightarrow{d} \chi^2(\#\text{moments} - \#\text{parameters}). \]

We solve the program in (14) using the differential evolution algorithm proposed by Storn and Price (1997). As Price, Storn, and Lampinen (2005) suggest, the algorithm is an efficient global optimizer, and should therefore be able to avoid local minima.
References


Doshi, Hitesh, 2012, The term structure of recovery rates, Discussion paper SSRN.


Glover, Brent, 2012, The expected cost of default, Discussion paper SSRN.


Huang, J., and M. Huang, 2003, How much of the corporate-treasury yield spread is due to credit risk, working paper Penn State and Stanford.


This figure offers an intuitive description of the chronology of the firm’s decision problem. At $t$ the shocks $s = (x, z)$ are realized, and the firm cash flow is determined based on the capital stock $k$ and the debt $b$, or $p = (k, b)$. Immediately after $t$, the firm chooses the new set of capital and debt, as the combination $p' = (k', b')$ that maximizes the value of the equity, given by the sum of the current cash flow, $d$, plus the continuation value.
Figure 2: CDS spreads and book leverage

This figure plots the average five-year CDS spread of ten decile portfolios constructed by sorting firms according to their book leverage. For each decile, we plot both the average CDS spread from the simulated panel (marked with a star) and the average CDS spread from the observed data (marked with a square). Data is from various sources and spans the period between January 2003 throughout December 2010.
Figure 3: Growth options and credit spread

At each date we consider two firms with the same ratio of debt to asset in place (i.e., the same book leverage). One of those two firms has just observed a positive realization of the idiosyncratic shock while the other has observed a negative realization. The first firm has growth options while the second does not. Because the shocks are persistent, the option to grow is due to the fact that the firm is on a high trajectory of the firm specific shock, and therefore expects also a positive shock in the next period. If that shock is large enough the firm will decide to invest. Therefore, since with one period debt the future investment, if there is one, is contextual to the repayment of the old debt, high growth options are informative to bond-holders only because they convey information about future profitability. For this reason the relation between credit spread and growth options should be negative, after controlling for book leverage.
Table 1: Stochastic discount factor model estimation

This table presents the results of the estimation of the stochastic discount factor model. In panel A, we report the estimated parameters with their respective standard errors. In panel B, we compare the five moments conditions used to construct the objective function of the SMM: the mean and standard deviation of the Sharpe Ratio, the mean and standard deviation of the real one-year constant–maturity Treasury rate, as well as the autocorrelation of one year changes in the Treasury rate. The standard deviation of the Sharpe ratio is computed by bootstrapping the empirical sample 1000 times with replacements. In the left column (Data) we report the value of the moment condition computed from the observed empirical sample, while in the right column (Model) we report the moment conditions computed from the simulated sample. Data is from FRED Saint Louis and from Ken French’s website and spans the period between January 1956 throughout December 2010.

<table>
<thead>
<tr>
<th>Panel A: Parameters</th>
<th>Estimate</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systematic Productivity Autocorrelation $\rho_x$</td>
<td>0.873</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Systematic Productivity Volatility $\sigma_x$</td>
<td>0.010</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Personal Discount Rate $\beta$</td>
<td>0.989</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Risk Aversion Parameter $\gamma_0$</td>
<td>8.094</td>
<td>(5.888)</td>
</tr>
<tr>
<td>Counter-cyclicality Parameter $\gamma_1$</td>
<td>-2157.372</td>
<td>(715.645)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>E[Sharpe Ratio]</td>
<td>0.428</td>
<td>0.452</td>
</tr>
<tr>
<td>STD[Sharpe Ratio]</td>
<td>0.409</td>
<td>0.388</td>
</tr>
<tr>
<td>E[1-Year Treasury Rate]</td>
<td>0.017</td>
<td>0.017</td>
</tr>
<tr>
<td>STD[1-Year Treasury Rate]</td>
<td>0.023</td>
<td>0.023</td>
</tr>
<tr>
<td>AC[$\Delta$ 1-Year Treasury Rate]</td>
<td>-0.081</td>
<td>-0.081</td>
</tr>
</tbody>
</table>
Table 2: Firm model estimation
This table presents the estimation results of the firm model. In panel A, we report the 12 estimated parameters with their respective standard errors. In panel B, we compare the 14 moments conditions used to construct the objective function of the SMM: the average book leverage, the average five-year CDS spread, the annual default frequency, the ratio of years in which the leverage sorting is valid over the total number of years, and the average five-year CDS spread of ten portfolios constructed by sorting firms into book leverage deciles. At the bottom of the table we report the 10 leverage portfolios mean absolute pricing error, the Hausman J-statistics and the respective p-value in brackets. In the left column (Data) we report the value of the moment condition computed from the observed empirical sample, while in the right column (Model) we report the moment conditions computed from the simulated sample. Data is from various sources and spans the period between January 2003 throughout December 2010.

### Panel A: Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idiosyncratic Productivity Autocorrelation ( \rho_z )</td>
<td>0.630</td>
<td>(0.292)</td>
</tr>
<tr>
<td>Idiosyncratic Productivity Volatility ( \sigma_z )</td>
<td>0.442</td>
<td>(0.199)</td>
</tr>
<tr>
<td>Corporate Taxes ( \tau )</td>
<td>0.116</td>
<td>(0.224)</td>
</tr>
<tr>
<td>Equity Issuance Cost ( \varphi )</td>
<td>0.061</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Debt Adjustment Cost ( \theta )</td>
<td>0.086</td>
<td>(0.075)</td>
</tr>
<tr>
<td>Production Function ( \alpha )</td>
<td>0.826</td>
<td>(0.140)</td>
</tr>
<tr>
<td>Fix Cost ( f )</td>
<td>0.609</td>
<td>(0.282)</td>
</tr>
<tr>
<td>Distress Cost ( \xi )</td>
<td>0.189</td>
<td>(0.098)</td>
</tr>
<tr>
<td>Cost of Expansion ( \lambda_1 )</td>
<td>0.002</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Cost of Contraction ( \lambda_2 )</td>
<td>0.304</td>
<td>(0.157)</td>
</tr>
<tr>
<td>Bankruptcy Cost ( \eta )</td>
<td>0.499</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Recovery on Debt ( R )</td>
<td>0.314</td>
<td>(0.126)</td>
</tr>
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</table>

### Panel B: Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>E[Book Leverage]</td>
<td>0.431</td>
<td>0.419</td>
</tr>
<tr>
<td>E[5-year CDS Spread]</td>
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<td>1.293</td>
</tr>
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<td>1-year Default Frequency</td>
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<td>Valid Sortings</td>
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<td>0.994</td>
</tr>
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<td>E[Leverage Portfolio CDS Spread]</td>
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<td></td>
</tr>
<tr>
<td>1 Low Leverage</td>
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<td>0.670</td>
</tr>
<tr>
<td>2</td>
<td>0.760</td>
<td>0.794</td>
</tr>
<tr>
<td>3</td>
<td>0.861</td>
<td>0.866</td>
</tr>
<tr>
<td>4</td>
<td>1.007</td>
<td>0.934</td>
</tr>
<tr>
<td>5</td>
<td>1.083</td>
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<tr>
<td>6</td>
<td>1.042</td>
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<tr>
<td>7</td>
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<td>8</td>
<td>1.360</td>
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<tr>
<td>9</td>
<td>2.064</td>
<td>1.996</td>
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<tr>
<td>10 High Leverage</td>
<td>2.738</td>
<td>2.631</td>
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<td>Portfolios Absolute Mean Pricing Error</td>
<td>0.064</td>
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<td>Hausman J-Statistic ( J )</td>
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<td>4.103</td>
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<td>[p-value]</td>
<td></td>
<td>[0.13]</td>
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</table>
Table 3: Variants to the base-case model

This table presents the estimation results of variations of the firm model. In column (1) we report the parameters of the base model; in column (2) we report results of the model without financial distress (No Diss); in column (3) we report the parameters of the model without fixed costs (No Fixed); in column (4) we report the parameters of the model without adjustment costs to the capital stock (No Adj); in column (5) we report the parameters of the model without equity issuance cost and debt adjustment costs (No Iss). In Panel A we report the estimated parameters with t-statistics in parenthesis. In panel B, we compare the moments conditions used to construct the objective function of the SMM: the average book leverage, the average five-year CDS spread, the annual default frequency, the ratio of years in which the leverage sorting is valid over the total number of years. At the bottom of the table we report the 10 leverage portfolios mean absolute pricing error, the Hausman J-statistics and the respective p-value in brackets. Data is from various sources and spans the period between January 2003 throughout December 2010.

<table>
<thead>
<tr>
<th>Panel A: Parameters</th>
<th>Base (1)</th>
<th>No Diss (2)</th>
<th>No Fixed (3)</th>
<th>No Adj (4)</th>
<th>No Iss (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idiosyncratic Prod. Autocorr. $\rho_z$</td>
<td>0.630 (2.16)</td>
<td>0.609 (8.76)</td>
<td>0.928 (38.92)</td>
<td>0.716 (13.37)</td>
<td>0.654 (15.07)</td>
</tr>
<tr>
<td>Idiosyncratic Prod. Volatility $\sigma_z$</td>
<td>0.442 (2.22)</td>
<td>0.444 (6.75)</td>
<td>0.391 (14.45)</td>
<td>0.375 (8.96)</td>
<td>0.278 (7.26)</td>
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<tr>
<td>Corporate Taxes $\tau$</td>
<td>0.116 (0.52)</td>
<td>0.218 (2.57)</td>
<td>0.236 (8.82)</td>
<td>0.147 (3.58)</td>
<td>0.189 (6.15)</td>
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<tr>
<td>Equity Issuance Cost $\varphi$</td>
<td>0.061 (0.60)</td>
<td>0.023 (0.42)</td>
<td>0.003 (0.10)</td>
<td>0.021 (0.36)</td>
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<tr>
<td>Debt Adjustment Cost $\theta$</td>
<td>0.086 (1.15)</td>
<td>0.076 (3.44)</td>
<td>0.011 (0.64)</td>
<td>0.014 (0.58)</td>
<td></td>
</tr>
<tr>
<td>Production Function $\alpha$</td>
<td>0.826 (5.91)</td>
<td>0.889 (21.76)</td>
<td>0.410 (23.07)</td>
<td>0.860 (42.70)</td>
<td>0.895 (141.2)</td>
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<td>Fix Cost $f$</td>
<td>0.609 (2.16)</td>
<td>0.559 (15.17)</td>
<td>0.533 (12.30)</td>
<td>0.651 (23.57)</td>
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<tr>
<td>Distress Cost $\xi$</td>
<td>0.189 (1.93)</td>
<td>0.275 (5.45)</td>
<td>0.070 (1.65)</td>
<td>0.027 (2.16)</td>
<td></td>
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<tr>
<td>Cost of Expansion $\lambda_1$</td>
<td>0.002 (0.04)</td>
<td>0.228 (2.46)</td>
<td>0.002 (0.09)</td>
<td>0.014 (0.27)</td>
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<tr>
<td>Cost of Contraction $\lambda_2$</td>
<td>0.304 (1.93)</td>
<td>0.494 (6.20)</td>
<td>0.755 (13.79)</td>
<td>0.439 (7.72)</td>
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<tr>
<td>Bankruptcy Cost $\eta$</td>
<td>0.499 (4.17)</td>
<td>0.463 (6.24)</td>
<td>0.543 (14.40)</td>
<td>0.527 (4.92)</td>
<td>0.521 (16.30)</td>
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<tr>
<td>Recovery on Debt $R$</td>
<td>0.314 (2.49)</td>
<td>0.311 (6.25)</td>
<td>0.315 (6.57)</td>
<td>0.301 (4.78)</td>
<td>0.335 (3.16)</td>
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<tr>
<td></td>
<td>Data</td>
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<td>No Fixed</td>
<td>No Adj</td>
</tr>
<tr>
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<td>-------</td>
<td>-------</td>
<td>---------</td>
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</tr>
<tr>
<td>E[Book Leverage]</td>
<td>0.430</td>
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<td>0.474</td>
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<td>E[5-year CDS Spread]</td>
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<td>0.362</td>
<td>1.326</td>
</tr>
<tr>
<td>1-year Default Frequency</td>
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<td>0.518</td>
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<td>0.562</td>
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<td>Valid Sortings</td>
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<td>0.994</td>
<td>0.947</td>
<td>0.074</td>
<td>0.961</td>
</tr>
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<td>Portfolios Absolute Mean Pricing Error</td>
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<td>0.083</td>
<td>0.204</td>
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<td>0.094</td>
</tr>
<tr>
<td>Hausman J-Statistic</td>
<td>4.103</td>
<td>26.826</td>
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<td>7.042</td>
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<tr>
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<td>[0.00]</td>
<td>[0.00]</td>
<td>[0.13]</td>
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</table>
Table 4: CDS spreads and operating leverage

This table presents the estimation results of panel regressions of 5-year CDS spreads on book leverage and operating leverage. We define a proxy of operating leverage as the impact of fixed costs on cash flow (the difference between sales and EBITDA, over EBITDA). In the first two columns, labeled Data, we report results obtained from the empirical sample. In columns (3) and (4), labeled Model, we report results obtained from the simulated sample. This last set of results is obtained by estimating the regression parameters for each of the 50 simulated samples. The reported parameters are then computed by averaging across the 50 estimations. The standard errors are obtained as standard deviations of the 50 estimates of the parameters. All regressions include time fixed effects. The regressions based on the Data sample also include industry fixed effects, and have standard errors clustered at firm level.

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>Model</th>
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<tbody>
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<td></td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td>Constant</td>
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<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(-4.98)</td>
<td>(-2.50)</td>
</tr>
<tr>
<td>Book Leverage</td>
<td>0.035</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(9.04)</td>
<td>(0.83)</td>
</tr>
<tr>
<td>Operating Leverage</td>
<td>0.033</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(5.17)</td>
<td>(2.13)</td>
</tr>
<tr>
<td>Operating Leverage \times Book Leverage</td>
<td>0.020</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td></td>
</tr>
<tr>
<td>Time Fixed Effects</td>
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<td>X</td>
</tr>
<tr>
<td>Industry Fixed Effects</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Clustered SE</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>2007</td>
<td>2007</td>
</tr>
<tr>
<td>adjusted-R^2</td>
<td>0.413</td>
<td>0.414</td>
</tr>
</tbody>
</table>
Table 5: CDS portfolio sorting by book leverage and operating leverage

This table reports independent quartile portfolio sorting of CDS spreads by book leverage and operating leverage. In Panel A we report results obtained from the empirically observed data (*Data*), while in Panel B we report results for the simulated sample (*Model*). The sorting procedure in the case of the simulated sample involves first sorting in each time period of each one of the 50 simulated samples. Next, we average across time. Finally, the results reported are obtained by averaging across the 50 simulated samples.

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Data</th>
<th>Panel B: Model</th>
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<tr>
<td></td>
<td>Operating Leverage</td>
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<tr>
<td></td>
<td>Low</td>
<td>(2)</td>
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<tr>
<td>Low Book Leverage</td>
<td>0.540</td>
<td>0.645</td>
</tr>
<tr>
<td>(2)</td>
<td>0.746</td>
<td>0.650</td>
</tr>
<tr>
<td>(3)</td>
<td>0.880</td>
<td>0.996</td>
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<td>High Book Leverage</td>
<td>1.850</td>
<td>1.586</td>
</tr>
<tr>
<td></td>
<td>0.628</td>
<td>0.694</td>
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<tr>
<td>(2)</td>
<td>0.757</td>
<td>0.777</td>
</tr>
<tr>
<td>(3)</td>
<td>0.881</td>
<td>0.891</td>
</tr>
<tr>
<td>High Book Leverage</td>
<td>1.576</td>
<td>1.369</td>
</tr>
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</table>
Table 6: CDS spreads and market–to–book ratio

This table presents the estimation results of panel regressions of 5-year CDS spreads on book leverage and market–to–book ratio, \( Q \). In the first two columns, labeled \textit{Data}, we report results obtained from the empirical sample. In columns (3) and (4), labeled \textit{Model}, we report results obtained from the simulated sample. This last set of results is obtained by estimating the regression parameters for each of the 50 simulated samples. The reported parameters are then computed by averaging across the 50 estimations. The standard errors are obtained as standard deviations of the 50 estimates of the parameters. All regressions include time fixed effects. The regressions based on the \textit{Data} sample also include industry fixed effects, and have standard errors clustered at firm level.

<table>
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<tr>
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<th>Model (3)</th>
<th>Model (4)</th>
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<tbody>
<tr>
<td>Constant</td>
<td>0.016</td>
<td>-0.030</td>
<td>0.018</td>
<td>0.013</td>
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<tr>
<td></td>
<td>(4.33)</td>
<td>(-4.86)</td>
<td>(9.32)</td>
<td>(11.76)</td>
</tr>
<tr>
<td>Book Leverage</td>
<td>0.034</td>
<td>0.102</td>
<td>0.031</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td>(8.94)</td>
<td>(10.46)</td>
<td>(11.35)</td>
<td>(10.93)</td>
</tr>
<tr>
<td>( Q )</td>
<td>-0.009</td>
<td>0.007</td>
<td>-0.005</td>
<td>-0.004</td>
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<tr>
<td></td>
<td>(-8.62)</td>
<td>(4.02)</td>
<td>(-6.92)</td>
<td>(-8.37)</td>
</tr>
<tr>
<td>( Q \times \text{Book Leverage} )</td>
<td>-0.046</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-8.79)</td>
<td></td>
<td>(-4.18)</td>
<td></td>
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<tr>
<td>Time Fixed Effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Industry Fixed Effects</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clustered SE</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2007</td>
<td>2007</td>
<td>149053</td>
<td>149053</td>
</tr>
<tr>
<td>Adjusted-( R^2 )</td>
<td>0.444</td>
<td>0.505</td>
<td>0.755</td>
<td>0.761</td>
</tr>
</tbody>
</table>
Table 7: CDS portfolio sorting by book leverage and market–to–book ratio

This table reports independent quartile portfolio sorting of CDS spreads by book leverage and market–to–book. In Panel A we report results obtained from the empirically observed data (Data), while in Panel B we report results for the simulated sample (Model). The sorting procedure in the case of the simulated sample involves first sorting in each time period of each one of the 50 simulated samples. Next, we average across time. Finally, the results reported are obtained by averaging across the 50 simulated samples.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low</td>
<td>(2)</td>
<td>(3)</td>
<td>High</td>
<td>H – L</td>
<td>t-stat</td>
</tr>
<tr>
<td>Low Book Leverage</td>
<td></td>
<td>1.215</td>
<td>0.788</td>
<td>0.691</td>
<td>0.510</td>
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<tr>
<td>(2)</td>
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<td>1.635</td>
<td>1.026</td>
<td>0.739</td>
<td>0.519</td>
<td>-1.116</td>
<td>(-2.93)</td>
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<tr>
<td>(3)</td>
<td></td>
<td>1.766</td>
<td>1.234</td>
<td>0.959</td>
<td>0.652</td>
<td>-1.114</td>
<td>(-2.75)</td>
</tr>
<tr>
<td>High Book Leverage</td>
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<td>4.068</td>
<td>2.450</td>
<td>1.404</td>
<td>0.668</td>
<td>-3.400</td>
<td>(-3.46)</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Market to Book Ratio</th>
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<th></th>
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<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Low</td>
<td>(2)</td>
<td>(3)</td>
<td>High</td>
<td>H – L</td>
<td>t-stat</td>
</tr>
<tr>
<td>Low Book Leverage</td>
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<td>0.901</td>
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<td>0.707</td>
<td>0.603</td>
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<td>(3)</td>
<td></td>
<td>2.201</td>
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<td>0.748</td>
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<td></td>
<td>2.964</td>
<td>2.288</td>
<td>1.905</td>
<td>1.807</td>
<td>-1.112</td>
<td>(-7.47)</td>
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</table>
Table 8: CDS spreads and growth opportunities

This table presents the estimation results of panel regressions of 5-year CDS spreads on book leverage, present value of asset in place (PVAP), present value of growth opportunities (PVGO), and market-to-book ratio. All results are obtained by estimating the regression parameters for each of the 50 simulated samples and subsequently averaging across the 50 estimations. The standard errors are obtained as standard deviations of the 50 estimates of the parameters. All regressions include time fixed effects.

<table>
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<th>(3)</th>
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<td></td>
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<td>(7.82)</td>
<td>(9.20)</td>
<td>(8.78)</td>
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<td>(12.75)</td>
<td>(13.40)</td>
<td>(11.51)</td>
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</tr>
<tr>
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<td>-0.004</td>
<td>-0.011</td>
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<tr>
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<td>(-6.80)</td>
<td>(-5.61)</td>
<td>(-5.69)</td>
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</tr>
<tr>
<td>PVGO</td>
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<td>-0.006</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-7.22)</td>
<td>(-7.92)</td>
<td>(-2.16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q</td>
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<td>0.004</td>
<td></td>
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</tr>
<tr>
<td></td>
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<td>(4.12)</td>
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<td>X</td>
<td>X</td>
<td>X</td>
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<td>Observations</td>
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<td>149053</td>
<td>149053</td>
<td>149053</td>
<td>149053</td>
</tr>
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<td>Adjusted-R²</td>
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<td>0.768</td>
<td>0.755</td>
<td>0.538</td>
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Table 9: CDS spreads and lagged asset and debt values

This table presents the estimation results of panel regressions of 5-year CDS spreads on current and lagged values of asset and debt. In the first three columns, labeled Data, we report results obtained from the empirical sample. In columns (4) to (6), labeled Model, we report results obtained from the simulated sample. This last set of results is obtained by estimating the regression parameters for each of the 50 simulated samples. The reported parameters are then computed by averaging across the 50 estimations. The standard errors are obtained as standard deviations of the 50 estimates of the parameters. All regressions include time fixed effects. The regressions based on the Data sample also include industry fixed effects, and have standard errors clustered at firm level.

<table>
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<tr>
<th></th>
<th>Data</th>
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<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
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<td>0.073</td>
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<td>0.023</td>
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<td>(8.21)</td>
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<td>(5.95)</td>
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<tr>
<td>Book Leverage</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(8.76)</td>
<td></td>
<td></td>
<td>(11.02)</td>
<td></td>
<td></td>
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<tr>
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<td>-0.010</td>
<td>-0.009</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.002</td>
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<tr>
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<tr>
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<td>0.007</td>
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<tr>
<td>Lag Debt</td>
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
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<td>X</td>
<td></td>
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<td>0.451</td>
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<td>0.480</td>
<td>0.497</td>
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</table>
Table 10: Changes in CDS spreads and changes in leverage

This table presents the estimation results of panel regressions of changes in 5-year CDS spreads on changes in debt and changes in asset. In the first two columns, labeled Data, we report results obtained from the empirical sample. In columns (3) to (4), labeled Model, we report results obtained from the simulated sample. This last set of results is obtained by estimating the regression parameters for each of the 50 simulated samples. The reported parameters are then computed by averaging across the 50 estimations. The standard errors are obtained as standard deviations of the 50 estimates of the parameters. All regressions include time fixed effects. The regressions based on the Data sample also include industry fixed effects, and have standard errors clustered at firm level.

<table>
<thead>
<tr>
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<th>Data</th>
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<td>(3)</td>
<td>(4)</td>
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<td>-0.002</td>
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<td>(-0.45)</td>
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<td>(-0.73)</td>
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<td>0.019</td>
<td></td>
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<tr>
<td></td>
<td>(2.83)</td>
<td>(8.72)</td>
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<td></td>
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<td>-0.000</td>
<td>-0.001</td>
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</tr>
<tr>
<td></td>
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<td></td>
<td>(13.82)</td>
<td></td>
</tr>
<tr>
<td>Time Fixed Effects</td>
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<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Industry Fixed Effects</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Clustered SE</td>
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<td>131386</td>
</tr>
<tr>
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<td>0.365</td>
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<td>0.350</td>
</tr>
</tbody>
</table>