Firm policies and the cross-section of CDS spreads[1]

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November 18, 2013

[1]We thank Michael Brennan, Jan Ericsson, Brent Glover, Robert Kieschnick, Ali Ozdagli, Alex Triantis, Tony Whited, and Harold Zhang for helpful comments and seminar participants at the 2012 European Finance Association, Exeter University, the First ITAM Finance Conference in Mexico City, George Mason University, Georgia State University, Manchester Business School, Piraeus University Athens, University of Texas at Austin, University of Texas at Dallas, University of Warwick, Vienna University of Economics and Business. We are especially thankful to Zack Liu and Ben Zhang for excellent research assistance. All errors are our own.

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Abstract

We solve the credit spread puzzle with a structural model of firms policies that endogenously replicates the empirical cross–section of credit spreads. Structural estimation of the model's parameters reveals that the model cannot be rejected by the data, and that endogenous investment decisions are major determinants of CDS spreads. We also verify 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 credit risk, investments are negatively correlated with changes in CDS spreads.

JEL Classifications: G12, G32

1 Introduction

Leverage is the main determinant of credit spreads, and many structural models have been developed to explain variation in credit spreads with variation in leverage ratios (for example, Chen, Collin-Dufresne, and Goldstein (2009), Bhamra, Kuehn, and Strebulaev (2010), and Chen (2010)). An important, and perhaps necessary, restriction that the econometrician might impose on a structural model is suggested by Bhamra, Kuehn, and Strebulaev (2010), who show that considering a sensible *cross–sectional distribution* of leverage is crucial even if one is only interested in producing a model that *on average* generates realistic credit spreads, leverage ratios and default frequencies, and hence solves the "credit spread puzzle" of Huang and Huang (2003).

Realistic leverage dynamics can be reproduced only by jointly considering the financing and investment decisions of the firm (Leary and Roberts (2005) and Hennessy and Whited (2005)). Therefore we conjecture that investments should also be a critical part of a credit risk model as they might help in *endogenously* generating a realistic cross-sectional distribution of leverage.[1] Moreover, considering investment decisions is also important because it might help explain some of the variation in credit spreads. In fact, firms with the same leverage might have different credit spreads, because they are on different investment paths (have different growth options), and hence have different default probabilities.

In this paper, we develop a structural model of credit risk, in which heterogenous firms react to exogenous productivity shocks by making investment and financing decisions, subject to a number of frictions. The model therefore encompasses both dynamic capital structure decisions as in Fischer, Heinkel, and Zechner (1989) and dynamic investments as in Zhang (2005) and is flexible enough that it allows us to impose some cross-sectional restriction in the estimation process. Credit risk arises in the model because of the uncertainty that the shareholders will be willing to meet their obligations. Default is therefore an endogenous event. Given the optimal default policy and an exogenously specified pricing kernel, we obtain our measure of credit spread: the price (i.e., spread) of a five year credit default swap (CDS).[2]

[1] Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2013), include dynamic investments in their models in order to study the impact of asset composition (i.e., invested asset relative to growth options) on the riskiness of the debt. Conversely, we are interested in studying the impact that investment, through the financing gap (i.e., difference between investments and internal resources), has on the debt decision and hence the resulting credit risk.

[2] 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

We estimate the parameters of the model by simulated method of moments (SMM) using a sample of non–financial S&P 500 firms that have CDS contracts on their debt. Contingent on having specified a proper set of moment conditions, SMM allows us to produce an objective statistical test of the model. Naturally a successful structural model of credit risk should solve the "credit spread puzzle" of Huang and Huang (2003), while allowing the econometrician to impose a restriction on the cross-section as in Bhamra, Kuehn, and Strebulaev (2010). Therefore, we specify two sets of moment conditions: first, we demand 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 require 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): the model can accurately reproduce the average CDS of all leverage portfolio. Fourth, we find that having a dynamic investment policy is a central requirement for the ability of the model to match the data. A version of the model whit fixed asset is, in fact, rejected by the data and unable to overcome another limitation of structural models that was originally highlighted by Huang and Huang (2003) in that it cannot generate reasonable credit spreads for firms that have very low leverage (high credit standing). Finally, we find that frictions that have been found to be very important determinant of leverage dynamics, such as transaction costs related to external financing, appear to play a minor role in influencing the credit risk of a firm.

The results described above, which are produced using variation in leverage as a source of conditional information, outlines the importance of considering variation in asset dynamics in characterizing the cross-sectional distribution of credit spreads. 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 exhibit mean-reversion. This generates persistence and mean-reversion in the firm's profitability. Second,

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).

adjustments to the capital stock incur asymmetric costs, as for example in Hennessy and Whited (2005) and Zhang (2005). While in good states of the world, the option to grow (i.e., making investments in the future) is valuable to bondholders as it is indicative of future profitability and solvency, in bad states of the world, having not realized the option to grow is valuable to bondholders as it spares the possibly large downsizing costs.

As Hennessy and Whited (2005) suggests, investigating the impact of conditional information that is not used in the estimation procedure gives "a measure of the success of the out–of–sample performance of the model." Therefore, we investigate how variation in credit spreads is associated to observable characteristics that are a direct consequence, in the model, of dynamic choices that firms make about their asset structure. 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). We investigate these relationships by juxtaposing a sample of empirically observed firms to a simulated economy.

Based on our model, we expect and find, a positive relation between credit spreads and the 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 also anticipate, 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. Moreover, 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, thus delivering a negative relationship between changes in credit spreads and investments. 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. Furthermore, 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. Chen (2010) show the importance of considering pro-cyclical recovery rates. Bhamra, Kuehn, and Strebulaev (2010) highlight the benefit of 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. Relative to these papers, we concentrate our attention on the cash flow generating process, while retaining the variation in risk premia; 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 *unconditional* distribution through the investment channel.

Two very recent papers, by Arnold, Wagner, and Westermann (2012) and Kuehn and Schmid (2013), 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 (2013) 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 our paper is that in their paper the actual cross-section of firms is used as a starting point for the simulated sample, while in our the distributions of leverage and asset value are endogenously generated. Our model shares many features with the one proposed by Kuehn and Schmid (2013). 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 (2013), we estimate the parameters of our model by simulated method of moments and use data on an economically important panel of firms. Most importantly, our approach highlights the importance of considering cross-sectional restrictions, as for example in Bhamra, Kuehn, and Strebulaev (2010), when attempting to solve the credit spread puzzle. A significant benefit of which is to provide new insights on cross-sectional pricing relationships, as opposed to solely 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 that of Hennessy and Whited (2007) in the description of the firm's decisions, and to those of Berk, Green, and Naik (1999), Zhang (2005) and Gomes and Schmid (2010) in the choice of a reasonably simple structure for pricing corporate securities.

In what follows, we first characterize an economy composed by heterogenous firms in which the preferences of risk averse investors are summarized by an exogenously specified stochastic discount factor. Then, we describe the firm's decisions. The model is solved using standard dynamic programming techniques and, when possible, we refer to the terminology, notation, and results by 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 economy 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 $Q_z(z_j, z_j')$. 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 $Q_x(x, x')$.

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, $Q(s, s')$, 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).

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

[3] A fixed cost proportional to capital stock is similar to what is assumed by Carlson, Fisher, and Giammarino (2004), Cooper (2006), and Kuehn and Schmid (2013).

economically and for accounting purposes at a constant rate $\delta > 0$.[4] 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

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

where $0 < \Lambda_1 < \Lambda_2$ model costly reversibility, and $\mathbf{1}_{\{.\}}$ is the indicator function. For convenience of estimation and economic interpretation, we reformulate the two cost reversibility parameters in the following way: $\Lambda_1 = \lambda_1/\delta$ and $\Lambda_2 = \lambda_2/\delta$. We will report the estimates of λ_1 and λ_2. The economic interpretation of λ 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 $t+1$. If the firm is solvent, the market value of such bond, $D(s, p')$, depends on the current state s and on the choices of the debt and the capital stock, $p' = (k', b')$, that are made after observing the shocks.

Changing the debt level entails a direct adjustment cost, $q(b, b') = \theta|b' - b|$, where $\theta \geq 0$.[5] Since the issuance decision is contemporaneous to repayment of the nominal value of old debt b, the debt decision generates a net cash flow equal to $D(s, p') - b - q(b, b')$.

We assume a very simple linear corporate tax function with rate τ.[6] The tax code allows deduction of the depreciation of the asset in place, δk, and of the interest expenses from the taxable income.[7] 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

[4]Because in the estimation procedure δ and f cannot be separately identified, δ will be set equal to an exogenous value of 0.12. We keep both parameters in the model to ease the economic interpretation of our results.

[5]Notably, this cost is defined neither as a proportion of the repurchased debt nor of the of the newly issued debt, as it is for instance in Fischer, Heinkel, and Zechner (1989), Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010).

[6]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 τ is analyzed.

[7]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.

value of the interest payment, $PI(s,p') = b' - D(s,p')$, can be expensed when the new debt is issued at time t. In case of linear 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

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

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 some 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 of the capital that is injected by the shareholders.

The equity payout is therefore equal to

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

where the terms in the first square bracket represent the after–tax cash flow from operations, inclusive of the distress cost 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

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

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 $\varphi \geq 0$.

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'. We assume that M is a continuous function of both arguments.

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:

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

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 or in default,

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

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, $\pi' = \pi(s', k')$, the depreciated book value of the asset, and the tax shield from depreciation, all net of a proportional bankruptcy cost, η. Hence, the current value of the debt, at the time it is issued, equals

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

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

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

Because the interest is deductible only if the firm is not in default, the expectation term is the conditional price of a default contingent claim.

In Appendix A, we prove the existence of the solution of the program given by the Bellman operator in equation (3), subject to the constraints in equations (5) and (6). The model is solved numerically by simultaneously finding the optimal value of S, D and PI. We describe the numerical approach in Appendix B.

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 periodically 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 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

$$\begin{aligned}\mathcal{P}_n(s,p,p') &= \mathcal{P}_n(s_t,p_t,p_{t+1})\\ &= \mathbb{E}_{s_t}\left[\mathcal{H}(s_{t+n-1},s_{t+n})\omega(s_{t+n},p_{t+1})\prod_{j=1}^{n-1}\mathcal{H}(s_{t+j-1},s_{t+j})\left(1-\omega(s_{t+j},p_{t+1})\right)\right]\end{aligned}$$

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

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

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. This is an important point to note because, when estimating the parameters, we ask the model to price a CDS contracts with a five year maturity. To do so we need to compute the five year cumulative default probability, and we are therefore assuming that the firm's choice of debt and capital would not change with the aggregate and idiosyncratic shocks. To assure that this assumption is not overly stringent, we will avoid the problem entirely, and repeat the estimation procedure using a one year CDS as the reference security.

Finally, the CDS spread is

$$cds(s,p,p') = (1-R)\frac{\sum_{n=1}^{T}\mathcal{P}_n(s,p,p')}{\sum_{n=1}^{T}\left(\mathcal{P}_n(s,p,p')+\mathcal{S}_n(s,p,p')\right)} \tag{7}$$

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 Professor Kenneth 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 Professor 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 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 D.

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

$$z' = (1 - \rho_z)\overline{z} + \rho_z z + \sigma_z \varepsilon'_z. \tag{8}$$

The second source of risk, x, also follows an auto-regressive process:

$$x' = (1 - \rho_x)\overline{x} + \rho_x x + \sigma_x \varepsilon'_x. \tag{9}$$

In the above equations, for $i = x, z$, $|\rho_i| < 1$ and ε_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 ε_z are uncorrelated across firms and time and are also uncorrelated with the aggregate shock, ε_x. We assume that the parameters ρ_z, σ_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 σ_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 (see Appendix A).

Finally, following Zhang (2005), we specify the stochastic discount factor (SDF) as

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

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 $\gamma_2 < 1$.[8]

We estimate the parameters that affect the SDF and the aggregate source of risk separately from the parameters that govern the idiosyncratic source of risk and the trade-offs within the firm. We 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 (ρ_x and σ_x), and the three parameters that govern the stochastic discount factor (β, γ_1 and γ_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,[9] the mean and standard deviation of the one–year constant–maturity real 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, ρ_x and σ_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

[8] Given our assumptions, the yield of a risk–free zero coupon bond is $1/\mathbb{E}_s[M(s,s')]$, where $\mathbb{E}_s[M(s,s')] = \beta e^{\mu(x)+\sigma(x)^2/2}$, with $\mu(x) = g(x)(1-\rho_x)(x-\overline{x})$ and $\sigma(x) = g(x)\sigma_x$.

[9] The model allows to analytically compute the Sharpe ratio for each state of the world, therefore the moments can be obtained directly from the average and standard deviation of the simulated values. This is not possible with empirically observed data. The average standard deviation is obtained as the ratio of the excess average market portfolio return to the standard deviation of the market portfolio returns in the sample. We obtain the standard deviation of the Sharpe ratio by bootstrapping the empirical sample 1,000 times with replacements.

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.

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. Because the depreciation rate and the fixed cost parameters could not be separately identified, we fix the depreciation rate δ at 12% to approximate the average depreciation rate in the data, and estimate all the remaining parameters by SMM.[10]

We set up our estimation to achieve two simultaneous and complementary 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 must generate a realistic cross section of credit spreads. In order to do so, we include, among the other moment conditions, 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 a representative cross section, we add a penalty moment condition 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).[11]

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

[10]A value of 12% for δ is in line with the choice made by several authors, for example Zhang (2005) and Gomes and Schmid (2010).

[11]We construct book leverage measures in the empirical sample despite the fact that the model does not restrict asset and liabilities, so that in the simulated firms can be operational with more liabilities than capital stock (while the market leverage is always lower than one). We do this because our cross–sectional analysis in Section 10 is based on book leverage, for reasons that we clarify in Section 5.2.1. Results of the model estimation using market leverage, instead of book leverage, are qualitatively and quantitatively very close to those presented in the paper and are available upon request.

not exclusively, a BBB one), as for example Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), and Kuehn and Schmid (2013). 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 *steady–state* 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 then the aggregate shock, 0.630 versus 0.873, and more volatile, 0.442 versus 0.010. Both parameter estimates are statistically significant.

The estimated corporate tax rate, τ, (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).[12]

The estimated equity issuance cost, φ, 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, θ, 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 α 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 (2013) set α

[12]The net tax benefit to debt estimated by Graham (2000) is 0.132 and is obtained as $(1-\tau_D)-(1-\tau_C)(1-\tau_E)=(1-0.296)-(1-0.350)(1-0.120)$, where τ_E is the personal tax rate on equity flows, τ_D is the personal tax rate on debt flows, and τ_C is the corporate tax rate.

to 0.65 in a model very similar to ours. However there are large bounds around those figures: estimates for α vary between 0.30, as in Zhang (2005) to 0.75, as in Riddick and Whited (2009).[13] We obtain an estimate for the fixed cost parameter, f, equal to 0.609. The figure is far from that used by Kuehn and Schmid (2013), 0.02 at quarterly frequency (0.08 at annual frequency), and close to the one in Cooper (2006) who uses 0.48. Carlson, Fisher, and Giammarino (2004) produce a much higher estimate, 1.54, although with a different specification of the production technology. 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 (2013) 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 σ_y, α and f. In our estimation, all of them are quite large. In unreported estimation experiments, we fixed either α 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, η, is 0.499. Similar to the case of the production function parameter, there is not a very strong consensus on what this parameter should be. Gomes and Schmid (2010) use 0.25 (although in a specification where the cost is proportional only to the depreciated value of the asset and there is a fixed dead weight cost of liquidation); 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 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, λ_1, is close to zero and statistically insignificant. The disinvestment cost parameter, λ_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

[13] Gomes (2001) sets α to 0.3, Hennessy and Whited (2005) estimate a value of α equal to 0.551, while Hennessy and Whited (2007) estimate a value of 0.620. Gomes and Schmid (2010) use 0.65.

(30% of the disinvestment), thus leading to a cash inflow of 0.880. Finally, the distress cost parameter, ξ, 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 ξ, 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 a financial loss of $v < 0$ is realized: if the firm chooses the first option (i.e., it liquidates 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* 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.[14]

[14] 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 shows 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 ($k = 3$). 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 is $-v\xi + h(I,k) = 0.0260$. 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 λ_2 or φ.

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.

The model is also successful on the front of generating a realistic cross section of CDS spreads. 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 convex).

Overall, the model cannot be rejected by the data. The test of over–identifying 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).

4.2.3 Dynamic Investments versus Fixed Assets

In this section we investigate the contribution of considering dynamic investment policies to the ability of the model to fit the data. We estimate two versions of the model in which the firm asset is kept constant: investments are forced to be equal to the economic depreciation.

In the first version (Fixed Asset) of the model all firms are constrained to have the same capital stock. In the second version (Fixed Asset Uniform) we randomly assign different asset levels to different firms, so that firms' capital stocks have a uniform cross–sectional distribution in each simulated sample.

Results of the estimation exercise are presented in Table 3. In Panel A we report the estimated parameters of the two fixed asset versions of the model and compare them to the estimates from the basic model. In Panel B we compare the moment conditions and report the model statistics. It is immediately obvious that the model with fixed asset has a poor fitting: both versions are rejected by the data according to the Hausmann test. Both versions require a higher leverage ratio to match the average credit spread, even though they need higher bankruptcy cost and lower recovery rates, as is shown in Panel A. As shown in Figure 3, where we display the book leverage of the ten leverage portfolios, none of the models (the base model included) can reproduce an exact cross-sectional distribution of leverage. All three models come relatively close in producing firms with low leverage, but differ vastly on the opposite end, with the basic model coming the closest to producing simulated sample that matches the right tail of the empirical leverage distribution.

The cause of the rejection by the data of the fixed asset models can be easily identified when we consider the cross–sectional distribution of CDS spreads. As was pointed out by Huang and Huang (2003), traditional structural models fail to be able to generate enough credit risk for firms with very good credit rating. Similarly in our estimation exercise we find that the model with static assets is not able to generate sufficient levels of CDS spreads for top 30% of the firm in credit standing (low leverage firms). As a result, although the average CDS spread is very close to average in the empirical sample, the cross–sectional average pricing error (across all ten portfolio) is relatively large for both version of the fixed asset model. Finally, only the version with uniformly distributed asset across firms is able to generate enough dispersion in the simulated sample to create the ten leverage portfolios.

In summary, allowing for dynamic investments gives the model the ability to not only match the unconditional moments, but also to generate a better cross-sectional distribution of leverage, as suggested by Leary and Roberts (2005) and Hennessy and Whited (2005), and credit spreads.

4.2.4 Robustness Checks: One-year CDS Contracts

In the main estimation procedure we have decided to estimate the model's parameters using a 5-year maturity (tenor) for the reference CDS contract. This choice is entirely driven by the fact that these contracts are the most liquid and therefore guarantee a large number of observations. A larger number of observation guarantees less noise in the estimation of the averages and covariances of the empirical moments. Similarly, since later in the paper we intend to cross–validate the model by running standard regressions where the dependent variable is the CDS spread, it is important that we have as many observations as possible.

Nonetheless, the model's underlying security is a one-year bond and, as we noted in Section 2.4, the prices of CDS contracts are obtained by keeping fixed the firm's policy. It would seem natural to estimate the model's parameters by pricing one-year CDS contracts, as opposed to five year ones.

In this section we present results of an estimation that uses a one-year tenor for the reference CDS. Results are reported in Table 4. At first glance, the estimated parameters are very similar to those obtained calibrating the model with the sample of five year CDS prices: the firm productivity parameters are very close, and so are the bankruptcy and recovery parameters. There are a few notable differences: the idiosyncratic volatility parameter is smaller at 0.309, relative to 0.442; taxes and the contraction cost are estimated at about 0.199 and 0.589, which is about twice the magnitude reported in the previous table; finally, the distress cost coefficient is practically zero, while it was 0.189 in base case scenario.

These differences seem to make one significant impact in the ability of the model to fit the data: to be able to describe well the cross section and the average default probability, the model requires a higher leverage than what we observe in the sample (0.489 relative to 0.430, respectively). Overall, the success of the exercise is mixed: on the one hand the pricing errors are small at 8.1 basis points; on the other hand the model is rejected by the data. This is mainly due to the fact that we have a lower number of observations and more noise in the empirical moments estimates. One remarkable example is the fact that the cross section of leverage portfolios does not present a monotonically increasing spread curve: portfolio 7 has a significantly lower average CDS spread than portfolios 6 and 8.

4.2.5 Robustness Checks: Alternate Specifications

In this section we discuss the impact of changing some key features of our model by repeating 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 impacts the overall ability of the model to fit the moment conditions, or changes 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, ξ; the role of fixed costs, f; the impact of real adjustment costs, λ_1 and λ_2; the role of financing frictions, in the form of equity floatation costs, φ, and debt adjustment costs, θ. The results of the five estimation exercises are reported in Table 5.

In the first alternate specification, we exclude financial distress costs (and therefore the state of financial distress) by setting ξ equal to zero. The goodness of fit of this model is lower than the base case scenario and the model is now 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 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 linked 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 component in the estimation exercise, other costs increase: 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, λ_1 and λ_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 (the parameter is in fact 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 equally 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. Asset adjustment costs seem relevant only when it comes to contraction, while expansion costs do not seem to be that crucial. 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).

4.2.6 Robustness Checks: Subsamples

In this section we discuss the impact of considering different aggregate economic conditions. We repeat the estimation exercise separately for the years 2003-2006 and for the years 2007-2010, thus separating the sample in two periods: one that contains the crisis and one that does not. Because the performance of firms during the second period is heavily conditioned by the economic crisis of 2007-2008, this experiment should give us a good understanding of the ability of the model to adapt to different conditions.

We report results of these estimation in Table 6. From Panel A, we note that some of the parameters are different across the two estimations. The autocorrelation of the idiosyncratic productivity shock is higher in the non-crisis period while the opposite is true for the volatility parameter. Thus, the estimation procedure is able to identify aggregate economic conditions by adjusting the parameters of the idiosyncratic productivity shock.

On the firm front the tax-parameter is higher in the pre-crisis period, signaling a higher benefit of holding debt when the economic environment is favorable. The parameters that represent adjustment costs to the financing policy (through debt or equity) are instead higher in the crisis period, as one could expect. The cost of expansion parameter is higher and significant in the pre-crisis period. The fix cost and the distress cost parameters are also higher in the crisis period, indicating that the firms operations appear riskier in an economic downturn. Finally, while the bankruptcy cost remains virtually unchanged, the recovery rate on par is much higher in the crisis period than it is in the more tranquil time.

From Panel B, we note that the overall ability of the model to match the moment conditions is relatively good in both sub–periods. In both periods the model does an accurate job at capturing the average leverage and credit spread. Possibly the only dimension in which the model has difficulty reconciling the data is the default frequency: the model over–estimates the default frequency in the crisis period by a significant amount.

Overall, in both sub-periods, the model is again not rejected by the data. This seems particularly noteworthy given the relatively large average pricing error in the crisis-period, when the cross section of credit spreads is particularly steep relative to leverage.

5 CDS Spreads and Firm Policies

The results described in the previous section, which are produced using variation in leverage as a source of conditional information, outlines the importance of considering variation in asset dynamics in characterizing the cross-sectional distribution of credit spreads. The past, current, and future investment choices are expected to impact credit risk because of two key aspects of the model. First, firm's profitability, because of mean-reversion in the productivity shocks, exhibits persistence. Second, the firm incurs asymmetric adjustment costs to the capital stock. While in good states of the world, the option to grow (i.e., making investments in the future) is valuable as it is indicative of future profitability and solvency, in bad states of the world, having not realized the option to grow is valuable as it spares the possible large downsizing costs.

Following Hennessy and Whited (2005), as an "out–of–sample" test of the model, we study how variation in credit spreads is associated to observable characteristics that are a direct consequence, in the model, of dynamic choices that firms make about their asset structure. 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). We investigate these relationships by juxtaposing a sample of empirically observed firms to a simulated economy.

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). Because of restrictions in the functional form of the production function, we adopt a particular definition of operating leverage at the end of period $]t-1,t]$ as the ratio of fixed production costs to EBITDA

$$\mathrm{OPL}(s,p) = \frac{e^{x+z}k^{\alpha} - \pi(s,k)}{\pi(s,k)} = \frac{fk}{\pi(s,k)}. \tag{11}$$

The equivalent to equation (11) in the observed data is given by the difference between sales and EBITDA, over EBITDA.[15]

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 7 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 parameter estimates. 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 8 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.

[15] Note that this is partly at odds with conventional definitions of operating leverage (percentage change of sales divided by percentage change of EBITDA), which are generally estimated in a regression approach. Unavailability of a long time series for the observed data precludes us from following this traditional approach.

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 4. There are two basic mechanisms that generate growth options: persistency of firm specific shocks and decreasing return to scale. 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 (the decision to invest will also depend on the realization of 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.[16]

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 9 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 *Data*, we report results obtained from the empirical sample. In columns (3) and (4), labeled

[16]This effect is what is reproduced also by Carlson, Fisher, and Giammarino (2004) in their model.

$Model$, 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 parameter estimates. 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, 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 10 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. 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 leverage. We find a similar pattern in the simulated sample, Panel B, with the exception of the highest leverage quartile for which the credit spread reduction is less marked (this portfolio is not very well populated).

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.

The economic forces that generate the negative relation between credit spreads and market–to–book ratios are the autocorrelation of the idiosyncratic productivity shocks and the curvature of the production function. A higher autocorrelation coefficient and a production function that exhibits decreasing returns to scale at a higher degree (smaller α), ought to make the relation between credit spreads and market–to–book ratios stronger, thus producing more negative regression coefficients.

In the spirit of Riddick and Whited (2009), we investigate those premises by conducting sensitivities of the regression coefficient by estimating additional regressions of CDS spreads on leverage and market–to–book ratios in simulated samples obtained by changing the model parameters of interest. Each sample is obtained by simulating the model with the set of estimated parameters reported in Table 2, but perturbing the autocorrelation of the idiosyncratic shock (ρ_z) and the production function parameter (α) in the interval $[-0.05, 0.05]$ around the estimates reported in Table 2, $\hat{\rho}_z = 0.630$ and $\hat{\alpha} = 0.826$. Because changing the optimal parameters produces more skewed samples, we standardize all variables before estimation. The results of these analyses, which are reported in Table 11, validate our conjectures: the regression coefficient on the market–to–book ratio is more negative in samples with higher ρ_z and lower α.

Notably, the reported negative conditional correlation between credit spreads and market–to–book ratios is apparently in contrast with the predictions of the theoretical models proposed by Arnold, Wagner, and Westermann (2012) and the calibration results presented by Kuehn and Schmid (2013). Although the predictions of our model line up with the empirical evidence, some discussion is required.

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 9 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 (2013).

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 market to book 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 market to book ratio has relatively higher equity valuation and better prospects. Since those are negatively related to the probability that the firm has financial problems, it leads to a negative correlation between credit spreads (risk) and market to book ratios. 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 manipulations $S_1/b_1' = S_2/b_2'$. The two firms have different market to book 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 (2013) find.

We conclude 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. We define S^{ng} (equity with no–growth) as the fixed point of the following functional equation

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

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 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:

$$Q = \frac{(b' + S)}{k'} = \frac{b'}{k'} + \mathrm{PVAP} + \mathrm{PVGO}\,. \tag{13}$$

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

From Equation (13) we can see 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.[17] We therefore defer to the simulated sample. Table 12 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 (after excluding book leverage) the sign of the coefficient in front of the market to book ratio

[17] 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.

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

Simplifying 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, because risk premia are countercyclical, an economic downturn decreases the value of future cash flows. This decreases the value of the option to grow, because the underlying asset 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 depending on the model calibration.

Although in our setting 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 9, 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* prevails.

5.3 Path dependency, 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 dependency.

This particular aspect of the model has been neglected in the discussions presented 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 13, 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 13 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 14 we report regression results of changes in CDS spreads 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 generated by endogenous investments 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 spreads, an important aspect to solve the credit spread puzzle.

Our estimation exercise shows 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 investment decisions also matter: current credit spreads are related to current and past values of capital stock and 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 Proof of existence of the solution of the model

The proof of the existence of the solution S of the functional equation (3) (together with the optimal policy F), subject to the constraints for D in equations (5) and for PI (6) mostly follows standard arguments by Stokey and Lucas (1989).

It is easy to prove that the choice set of the program in (3) is compact. As for k', given the current capital stock k, the firm cannot sell more than the current capital, or $k' \geq 0$, and it makes no economic sense to invest more than $\overline{k}$, such that $\pi(\overline{x}, \overline{z}, \overline{k}) - \delta\overline{k} = 0$, given the strict concavity of the production function, and $\overline{x}$ and $\overline{z}$ are the best possible outcomes for the systematic and the idiosyncratic shock, respectively.

Quite naturally, $b' \geq 0$. On the other hand, there is an upper bound for b', say $\overline{b}$, because there is a tradeoff between the positive effect that increasing the debt has on current year dividend (v, in equation (1), is increasing in both D and PI, and they are increasing in b', although at a decreasing rate), and the negative effect that it has on next year expected dividend (v is decreasing in b), and this effect is magnified by a factor $(1+\xi)$ if the after–tax cash flow is negative (which is the case if the debt is high), and by a factor $1+\phi$ if the net proceed from selling capital is insufficient. So, we may conclude that the choice set for k' and b' is compact. Then, we have the following

Lemma 1. *Under the stated conditions that the decision set is compact, Q has the Feller property, M is continuous, and ω is almost everywhere continuous, the functions D and PI are continuous in (s, p').*

To prove this result, we focus on D, as the same argument carries over to PI. In particular, we have to show that $D(s, p') = \int u(s', p')M(s, s')Q(s, ds')$ is continuous. By separating the two components of the payoff function u, this boils down to proving that the function $\int \omega(s', p')M(s, s')Q(s, ds')$ is continuous in (s, p'), where $\omega(s', p')$ is the default indicator function, which is bounded and is almost everywhere continuous (i.e., the set of the discontinuity points has zero measure). If this is true, then D is continuous because it is a linear combination of continuous functions.

For notational convenience, let define $H(s, s') = M(s, s')Q(s, s')$. Because M is continuous and the support of s and s' is compact, M is bounded. We need to prove that $f(s, p') = \int \omega(s', p')H(s, ds')$ is continuous. Of course, M does not create any concerns in this respect, given Q has the Feller property (see Lemma 9.5 in Stokey and Lucas (1989)). Because the state space is compact, there is a sequence $\{(s_n, p'_n)\}$ converging to (s, p'). We just need to prove that $|f(s_n, p'_n) - f(s, p')|$ converges to zero for $n \to \infty$. We observe that

$$|f(s_n, p'_n) - f(s, p')| \leq |f(s_n, p'_n) - f(s, p'_n)| + |f(s, p'_n) - f(s, p')|. \tag{14}$$

As for the second component in the right–hand–side of (14), we have

$$\begin{aligned}|f(s, p'_n) - f(s, p')| &= \left| \int \omega(s', p'_n) H(s, ds') - \int \omega(s', p') H(s, ds') \right| \\ &\leq \int |\omega(s', p'_n) - \omega(s', p')| \, H(s, ds').\end{aligned}$$

By separating the support of s' into the subset in which ω is continuous from the subset in which it is discontinuous, $|\omega(s', p'_n) - \omega(s', p')|$ converges to zero for $n \to \infty$ when in the first subset. In the second subset, the behavior of ω is not important because it has zero measure.

As for the first component in (14),

$$|f(s_n, p'_n) - f(s, p'_n)| = \left| \int \omega(s', p'_n) H(s_n, ds') - \int \omega(s', p'_n) H(s, ds') \right|$$
$$\leq \int \omega(s', p'_n) \, |M(s_n, s') Q(s_n, ds') - M(s, s') Q(s, ds')| \leq \overline{M} \int \omega(s', p'_n) \, |Q(s_n, ds') - Q(s, ds')| \, ,$$

where $\overline{M}$ is the maximum value of M.

Because Q has the Feller property, then it is continuous in the first argument. This can be proved by contradiction: Assume that Q is discontinuous in $\overline{s}$. Then, for an arbitrary continuous function g, the function $G(s) = \int g(s') Q(s, ds')$ would be discontinuous in $\overline{s}$.

Therefore, $|Q(s_n, ds') - Q(s, ds')|$ converges to zero for $n \to \infty$, and this concludes the proof of the lemma.

Proposition 2. *There is a unique solution S to the program in equations* (3)*,* (5)*, and* (6)*. S is increasing in $s = (x, z)$ and k, and is decreasing in b.*

To prove this proposition, define the operator T as follows:

$$(TS)(s, p) = \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \beta \mathbb{E}_s \left[m(s, s') S(s', p') \right] \right\} \right\},$$

where we have specified $M(s, s') = \beta m(s, s')$, with $\beta < 1$, so that the risk-free component of the stochastic discount factor is highlighted.[18]

First, we will prove that if S is a continuous function on the compact set for (s, p), also TS is continuous on the same compact set. Second, we will show that $S_1 \leq S_2$ implies $TS_1 \leq TS_2$. Third, we will show that for any $a \geq 0$, $T(S + a) \leq TS + \beta a$. Then, because the last two are the Blackwell sufficient conditions, if the operator T satisfies them it is a contraction and the fixed point exists and is unique because the set of continuous functions equipped with the sup-norm is a complete metric space.

We first show that $(TS)(s, p)$ is continuous for all (s, p). From Lemma 1, both D and PI are continuous. Therefore, v, w and d in (2) are continuous. Because the feasible set for p' is compact, using the Maximum Theorem (see Theorem 3.6 in Stokey and Lucas (1989)) the function

$$L(s, p) = \max_{p'} \left\{ d(s, p, p') + \mathbb{E}_s \left[M(s, s') S(s', p') \right] \right\}, \tag{15}$$

is continuous. Because $(TS)(s, p) = \max \{0, L(s, p)\}$, also TS is continuous.

As for monotonicity of the operator T, let S_1 and S_2 such that $S_1(s, p) \leq S_2(s, p)$ for all (s, p). Then the following is straightforward:

$$\begin{aligned}
(TS_1)(s, p) &= \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \mathbb{E}_s \left[M(s, s') S_1(s', p') \right] \right\} \right\} \\
&\leq \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \mathbb{E}_s \left[M(s, s') S_1(s', p') \right] \right\} \right\} = (TS_2)(s, p).
\end{aligned}$$

Lastly, let

$$\begin{aligned}
[T(S + a)](s, p) &= \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \beta \mathbb{E}_s \left[m(s, s') \left(S(s', p') + a \right) \right] \right\} \right\} \\
&= \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \beta \mathbb{E}_s \left[m(s, s') S(s', p') \right] \right\} + \beta a \right\} \\
&\leq \max \left\{ 0, \max_{p'} \left\{ d(s, p, p') + \beta \mathbb{E}_s \left[m(s, s') S(s', p') \right] \right\} \right\} + \beta a \\
&= (TS)(s, p) + \beta a.
\end{aligned}$$

Monotonicity of S with respect to $s = (x, z)$ is due to strict monotonicity of both π and Q with respect to x and z. Monotonicity of S with respect to k and b is based on

[18] The fact that M is bounded make this assumption harmless.

monotonicity of d in equation (2) with respect to these variables. This concludes the proof of the proposition.

Finally, the fact that the default indicator function, which has values in $\{0, 1\}$, is discontinuous only in a set with zero measure can be proved by observing that the change of value from 0 to 1 occurs where the continuous and strictly monotonic function L, defined in equation (15), is equal to zero. L is strictly monotonic because S is monotonic, Q is monotonic and π is strictly monotonic.

B 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 $\left\{b_j = j\frac{b_u}{N_b} \mid j = 1, \ldots, N_b\right\}$ with $N_k = 25$ and $N_b = 21$. 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.

C 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 ω, 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 $\mathcal{P}_i = H_{nd}^{i-1} H_d I_d$ and $\mathcal{S}_i = H_{nd}^{i} I_{nd}$, 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

$$cds = (1-R)\frac{\sum_{i=1}^{T} \mathcal{P}_i}{\sum_{i=1}^{T} (\mathcal{P}_i + \mathcal{S}_i)}$$

D 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

$$\hat{\theta} = \arg\min_{\theta} \left\{ G_N(\theta)' \, W_N \, G_N(\theta) \right\}, \tag{16}$$

where

$$G_N(\theta) = m_N - \frac{1}{J}\sum_{j=1}^{J} \widetilde{m}_n^j(\theta)$$

and $W_N = [N \operatorname{var}(m_N)]^{-1}$ is the efficient weighting matrix, m_N are the empirical moments based on N observations, $\widetilde{m}_n^j$ are the simulated moments based on n observations in each sample j. We calculate the efficient matrix $\operatorname{var}(m_N)$ by block bootstrapping, with replacement, the data 5000 times. The block bootstrap procedure draws firms first and then blocks of at least 2 fiscal years of data.

Following Pakes and Pollard (1989), standard asymptotic arguments can be applied so that for $N \longrightarrow \infty$, $\sqrt{N}(\hat{\theta} - \theta_0) \xrightarrow{d} \mathcal{N}(0, \Omega)$, 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 $\Lambda = N \, \text{avar}(m(\theta_0)) = N \, \text{avar}(\widetilde{m}(\theta_0))$. Γ is computed by numerically differentiating $G_N(\theta)$ around $\hat{\theta}$, and Λ 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

$$\frac{NJ}{1+J} G_N(\theta_0)' \, \Lambda^{-1} \, G_N(\theta_0) \xrightarrow{d} \chi^2(\#\text{moments} - \#\text{parameters}).$$

We solve the program in (16) 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 is able to avoid local minima.

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Figure 1: Model time line

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.

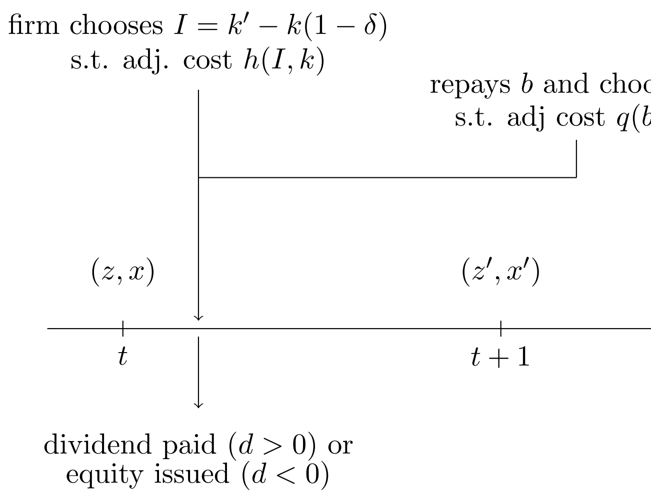

Figure 2: CDS spreads and book leverage

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.

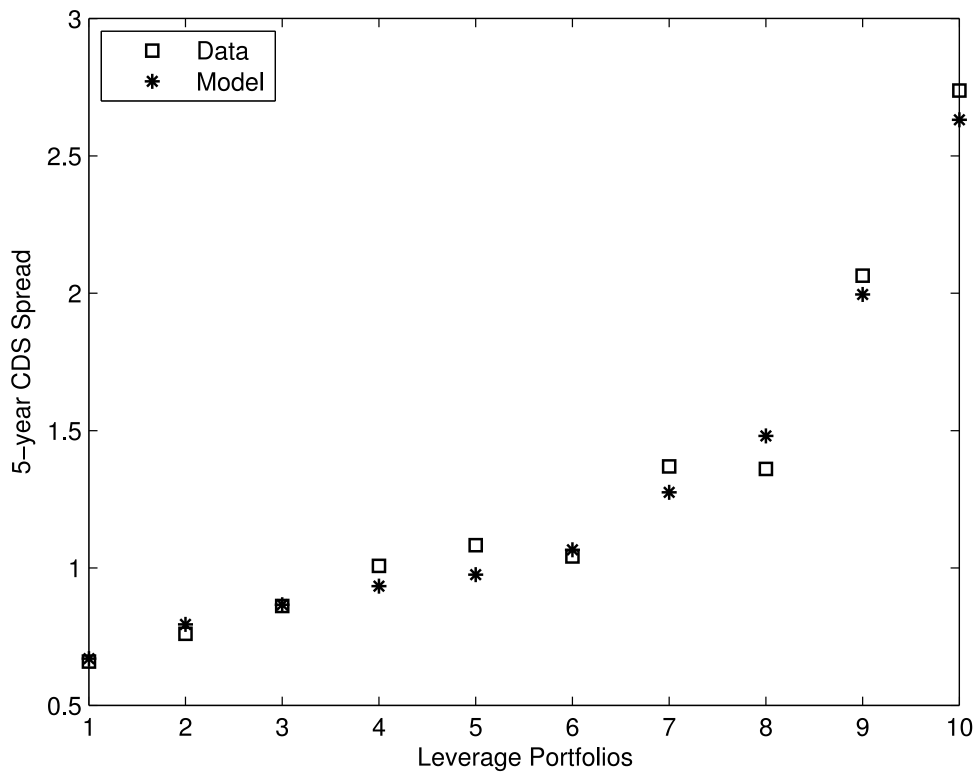

Figure 3: Book leverage portfolios

This figure plots the average book leverage of ten decile portfolios constructed by sorting firms according to their book leverage. For each decile, we plot both the average leverage from the observed data (marked with a square), the simulated panel from the base model (marked with a star) and the simulated panel from two versions of the model with fixed assets (marked with a circle and a pentagram). In the first version of the model, labeled *Fixed Asset*, we assign the same initial capital to all firms in each simulated economy. In the second version of the model, labeled *Fixed Asset Uniform*, each firm is assigned an initial level of capital that is drowned from the uniform distribution across the the support of all possible levels of assets. In both cases, each firm is allowed to make investments equal to the annual depreciation so that, in effect, their capital is fixed. Data is from various sources and spans the period between January 2003 throughout December 2010.

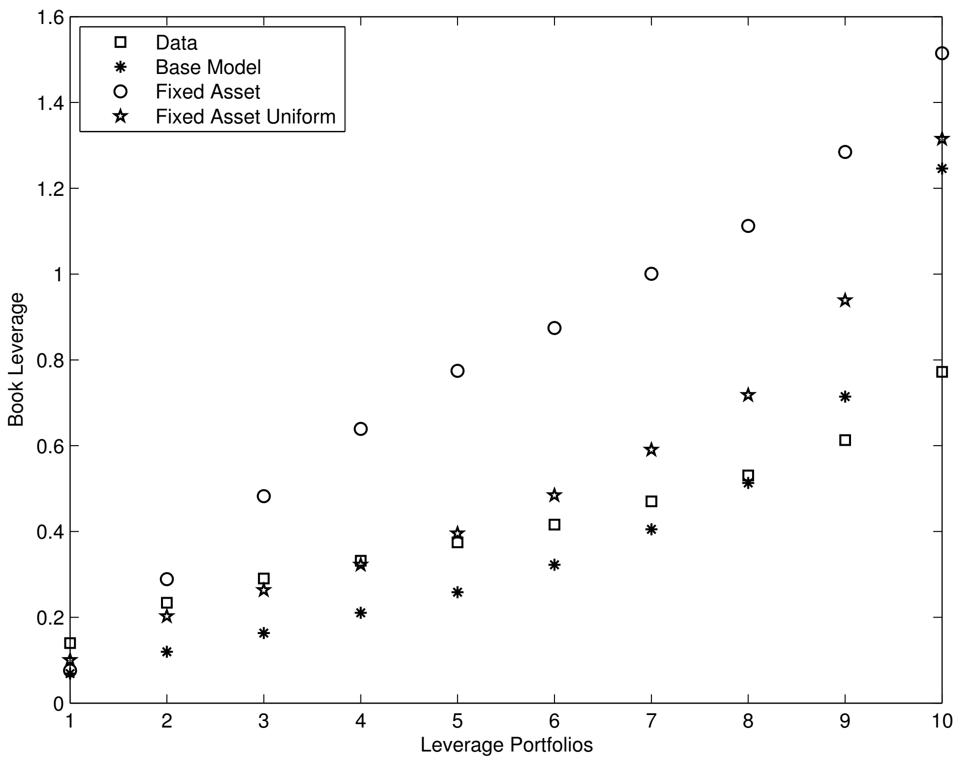

Figure 4: Growth options and credit spread

At a given 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.

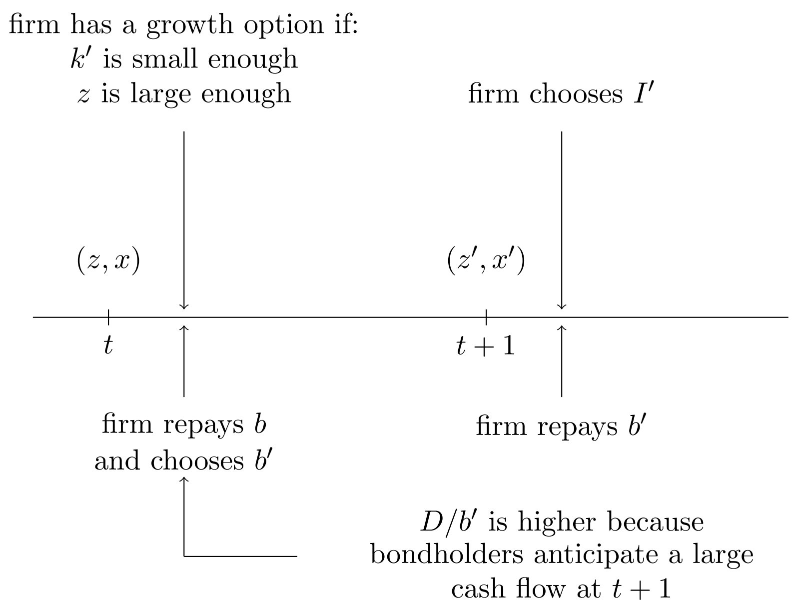

Table 1: Stochastic discount factor model estimation

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.

Panel A: Parameters			
		Estimate	s.e.
Systematic Productivity Autocorrelation	ρ_x	0.873	(0.048)
Systematic Productivity Volatility	σ_x	0.010	(0.000)
Personal Discount Rate	β	0.989	(0.012)
Risk Aversion Parameter	γ_0	8.094	(5.888)
Counter-cyclicality Parameter	γ_1	-2157.372	(715.645)
Panel B: Moments			
		Data	Model
E[Sharpe Ratio]		0.428	0.452
STD[Sharpe Ratio]		0.409	0.388
E[1-Year Treasury Rate]		0.017	0.017
STD[1-Year Treasury Rate]		0.023	0.023
AC[Δ 1-Year Treasury Rate]		-0.081	-0.081

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 conditions 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			
		Estimate	s.e.
Idiosyncratic Productivity Autocorrelation	ρ_z	0.630	(0.292)
Idiosyncratic Productivity Volatility	σ_z	0.442	(0.199)
Corporate Taxes	τ	0.116	(0.224)
Equity Issuance Cost	φ	0.061	(0.101)
Debt Adjustment Cost	θ	0.086	(0.075)
Production Function	α	0.826	(0.140)
Fix Cost	f	0.609	(0.282)
Distress Cost	ξ	0.189	(0.098)
Cost of Expansion	λ_1	0.002	(0.045)
Cost of Contraction	λ_2	0.304	(0.157)
Bankruptcy Cost	η	0.499	(0.120)
Recovery on Debt	R	0.314	(0.126)
Panel B: Moments			
		Data	Model
E[Book Leverage]		0.431	0.419
E[5-year CDS Spread]		1.299	1.293
1-year Default Frequency		0.491	0.521
Valid Sortings		1.000	0.994
E[Leverage Portfolio CDS Spread]:			
1 Low Leverage		0.659	0.670
2		0.760	0.794
3		0.861	0.866
4		1.007	0.934
5		1.083	0.975
6		1.042	1.066
7		1.370	1.276
8		1.360	1.481
9		2.064	1.996
10 High Leverage		2.738	2.631
Absolute Mean Pricing Error			0.064
Hausman J-Statistic			4.103
			[0.13]

Table 3: Dynamic Investment versus Fixed Asset

This table compares the estimation results of the base model (reported in Table 2) to estimation results of two versions of the model that feature fixed asset as opposed to dynamic investment. In the first version of the model, labeled *Fixed Asset*, we assign the same initial capital to all firms in each simulated economy. In the second version of the model, labeled *Fixed Asset Uniform*, each firm is assigned an initial level of capital that is drowned from the uniform distribution across the the support of all possible levels of assets. In both cases, each firm is allowed to make investments equal to the annual depreciation so that, in effect, their capital is fixed. In Panel A we report the estimated parameters with t-statistics in parenthesis. In panel B, we compare the 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 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.

Panel A: Parameters

		Base Model	Fixed Asset	Fixed Asset Uniform
Idiosyncratic Productivity Autocorrelation	ρ_z	0.630	0.884	0.601
		(0.29)	(0.10)	(0.03)
Idiosyncratic Productivity Volatility	σ_z	0.442	0.399	0.144
		(0.20)	(0.17)	(0.02)
Corporate Taxes	τ	0.116	0.109	0.244
		(0.22)	(0.05)	(0.08)
Equity Issuance Cost	ϕ	0.061	0.031	0.069
		(0.10)	(0.08)	(0.09)
Debt Adjustment Cost	θ	0.086	0.085	0.099
		(0.07)	(0.12)	(0.05)
Production Function	α	0.826	0.790	0.836
		(0.14)	(0.17)	(0.12)
Fix Cost	f	0.609	0.350	0.687
		(0.28)	(0.16)	(0.01)
Distress Cost	ξ	0.189	0.003	0.009
		(0.10)	(0.07)	(0.05)
Cost of Expansion	λ_1	0.002		
		(0.04)		
Cost of Contraction	λ_2	0.304		
		(0.16)		
Bankruptcy Cost	η	0.499	0.541	0.550
		(0.12)	(0.17)	(0.19)
Recovery on Debt	R	0.314	0.201	0.232
		(0.13)	(0.09)	(0.11)

Panel B: Moments				
	Data	Base Model	Fixed Asset	Fixed Asset Uniform
E[Book Leverage]	0.430	0.419	0.821	0.584
E[5-year CDS Spread]	1.298	1.293	1.255	1.247
1-year Default Frequency	0.491	0.521	0.491	0.622
Valid sortings	1.000	0.994	0.073	0.977
E[Leverage Portfolio CDS Spread]:				
1 Low Leverage	0.657	0.670	0.061	0.013
2	0.737	0.794	0.211	0.316
3	0.885	0.866	0.430	0.643
4	1.003	0.934	0.943	0.962
5	1.077	0.975	0.773	1.280
6	1.142	1.066	1.290	1.369
7	1.336	1.276	1.617	1.599
8	1.354	1.481	1.105	1.449
9	2.036	1.996	1.616	1.680
10 High Leverage	2.705	2.631	1.232	2.599
Absolute Mean Pricing Error		0.064	0.451	0.260
Hausmann J-Statistic		4.103	1137.1	166.2
		[0.13]	[0.00]	[0.00]

Table 4: Firm model estimation — 1 year CDS

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 one-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 one-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 conditions 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			
		Estimate	s.e.
Idiosyncratic Productivity Autocorrelation	ρ_z	0.627	(0.091)
Idiosyncratic Productivity Volatility	σ_z	0.309	(0.072)
Corporate Taxes	τ	0.199	(0.106)
Equity Issuance Cost	ϕ	0.041	(0.131)
Debt Adjustment Cost	θ	0.000	(0.030)
Production Function	α	0.866	(0.019)
Fix Cost	f	0.619	(0.051)
Distress Cost	ξ	0.004	(0.108)
Cost of Expansion	λ_1	0.017	(0.031)
Cost of Contraction	λ_2	0.583	(0.176)
Bankruptcy Cost	η	0.547	(0.093)
Recovery on Debt	R	0.302	(0.324)
Panel B: Moments			
		Data	Model
E[Book Leverage]		0.430	0.489
E[1-year CDS Spread]		0.740	0.757
1-year Default Frequency		0.491	0.515
E[Leverage Portfolio CDS Spread]:			
1 Low Leverage		0.360	0.336
2		0.421	0.449
3		0.551	0.540
4		0.491	0.562
5		0.640	0.613
6		0.633	0.668
7		0.862	0.715
8		0.683	0.851
9		1.278	1.007
10 High Leverage		1.410	1.386
Absolute Mean Pricing Error			0.081
Hausman J-Statistic			19.402
			[0.00]

Table 5: 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 Fix); 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 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 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.

Panel A: Parameters						
		Base (1)	No Diss (2)	No Fix (3)	No Adj (4)	No Iss (5)
Idiosyncratic Productivity Autocorr.	ρ_z	0.630	0.609	0.928	0.716	0.654
		(0.29)	(0.07)	(0.02)	(0.05)	(0.04)
Idiosyncratic Productivity Volatility	σ_z	0.442	0.444	0.391	0.375	0.278
		(0.20)	(0.07)	(0.03)	(0.04)	(0.04)
Corporate Taxes	τ	0.116	0.218	0.236	0.147	0.189
		(0.22)	(0.08)	(0.03)	(0.04)	(0.03)
Equity Issuance Cost	φ	0.061	0.023	0.003	0.021	
		(0.10)	(0.05)	(0.03)	(0.06)	
Debt Adjustment Cost	θ	0.086	0.076	0.011	0.014	
		(0.07)	(0.02)	(0.02)	(0.02)	
Production Function	α	0.826	0.889	0.410	0.860	0.895
		(0.14)	(0.04)	(0.02)	(0.02)	(0.01)
Fix Cost	f	0.609	0.559		0.533	0.651
		(0.28)	(0.04)		(0.04)	(0.03)
Distress Cost	ξ	0.189		0.275	0.070	0.027
		(0.10)		(0.05)	(0.04)	(0.01)
Cost of Expansion	λ_1	0.002	0.228	0.002		0.014
		(0.04)	(0.09)	(0.02)		(0.05)
Cost of Contraction	λ_2	0.304	0.494	0.755		0.439
		(0.16)	(0.08)	(0.05)		(0.06)
Bankruptcy Cost	η	0.499	0.463	0.543	0.527	0.521
		(0.12)	(0.07)	(0.04)	(0.11)	(0.03)
Recovery on Debt	R	0.314	0.311	0.315	0.301	0.335
		(0.13)	(0.05)	(0.05)	(0.06)	(0.11)

Panel B: Moments						
	Data	Base	No Diss	No Fix	No Adj	No Iss
E[Book Leverage]	0.430	0.419	0.467	0.635	0.474	0.440
E[5-year CDS Spread]	1.298	1.293	1.278	0.362	1.326	1.269
1-year Default Frequency	0.491	0.521	0.518	0.126	0.562	0.542
Valid sortings	1.000	0.994	0.947	0.074	0.961	0.969
E[Leverage Port. CDS Spread]:						
1 Low Leverage	0.657	0.670	0.579	0.596	0.645	0.637
2	0.737	0.794	0.765	0.313	0.801	0.805
3	0.885	0.866	0.885	0.858	0.871	0.906
4	1.003	0.934	0.972	1.015	0.963	0.948
5	1.077	0.975	1.047	0.935	1.067	1.024
6	1.142	1.066	1.145	1.286	1.225	1.097
7	1.336	1.276	1.257	1.208	1.343	1.303
8	1.354	1.481	1.445	1.371	1.546	1.460
9	2.036	1.996	1.845	1.713	1.895	1.790
10 High Leverage	2.705	2.631	2.405	1.940	2.480	2.414
Absolute Mean Pricing Error		0.064	0.083	0.204	0.079	0.094
Hausman J-Statistic		4.103	26.826	2193.8	18.738	7.042
		[0.13]	[0.00]	[0.00]	[0.00]	[0.13]

Table 6: Subsamples

This table presents the estimation results of the firm model in two separate sub-samples: 2003-2006 and 2007-2010 respectively. 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 columns labeled *Data* we report the value of the moment conditions computed from the observed empirical sample, while in the columns labeled *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			
		2003-2006	2007-2010
Idiosyncratic Productivity Autocorrelation	ρ_z	0.741	0.601
		(0.08)	(0.14)
Idiosyncratic Productivity Volatility	σ_z	0.245	0.441
		(0.03)	(0.10)
Corporate Taxes	τ	0.159	0.111
		(0.06)	(0.14)
Equity Issuance Cost	ϕ	0.029	0.051
		(0.09)	(0.08)
Debt Adjustment Cost	θ	0.024	0.099
		(0.06)	(0.07)
Production Function	α	0.882	0.847
		(0.21)	(0.11)
Fix Cost	f	0.565	0.648
		(0.12)	(0.03)
Distress Cost	ξ	0.005	0.072
		(0.14)	(0.15)
Cost of Expansion	λ_1	0.165	0.011
		(0.07)	(0.06)
Cost of Contraction	λ_2	0.512	0.522
		(0.27)	(0.15)
Bankruptcy Cost	η	0.546	0.549
		(0.11)	(0.18)
Recovery on Debt	R	0.454	0.210
		(0.22)	(0.32)

Panel B: Moments				
	2003-2006		2007-2010	
	Data	Model	Data	Model
E[Book Leverage]	0.422	0.460	0.431	0.440
E[5-year CDS Spread]	0.711	0.681	1.886	1.806
1-year Default Frequency	0.266	0.286	0.715	0.932
Valid sortings	1.000	0.980	1.000	0.986
E[Leverage Portfolio CDS Spread]:				
1 Low Leverage	0.446	0.308	0.867	0.872
2	0.367	0.378	1.107	1.132
3	0.478	0.442	1.291	1.330
4	0.509	0.514	1.497	1.517
5	0.584	0.559	1.569	1.564
6	0.571	0.631	1.712	1.651
7	0.756	0.709	1.916	1.886
8	0.815	0.831	1.892	2.166
9	1.075	0.966	2.997	2.554
10 High Leverage	1.414	1.312	3.996	3.152
Pricing error		0.055		0.174
J-stat		3.127		4.737
		[0.22]		[0.09]

Table 7: 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.

	Data		Model	
	(1)	(2)	(3)	(4)
Constant	-0.030	-0.023	0.002	0.002
	(-4.98)	(-2.50)	(1.01)	(1.78)
Book Leverage	0.035	0.019	0.013	0.010
	(9.04)	(0.83)	(8.73)	(10.73)
Operating Leverage	0.033	0.024	0.009	0.008
	(5.17)	(2.13)	(6.51)	(7.04)
Operating Leverage × Book Leverage		0.020		0.003
		(0.73)		(2.84)
Time Fixed Effects	X	X	X	X
Industry Fixed Effects	X	X		
Clustered SE	X	X		
Observations	2007	2007	149053	149053
adjusted-R^2	0.413	0.414	0.649	0.650

Table 8: 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.

	Panel A: Data					
	Operating Leverage					
	Low	(2)	(3)	High	H – L	t-stat
Low Book Leverage	0.540	0.645	0.763	1.012	0.472	(3.61)
(2)	0.746	0.650	0.866	1.770	1.024	(4.12)
(3)	0.880	0.996	1.054	1.953	1.073	(3.77)
High Book Leverage	1.850	1.586	1.820	3.398	1.548	(3.55)
	Panel B: Model					
	Operating Leverage					
	Low	(2)	(3)	High	H – L	t-stat
Low Book Leverage	0.628	0.694	0.767	1.059	0.424	(4.72)
(2)	0.757	0.777	0.965	1.615	0.858	(6.29)
(3)	0.881	0.891	1.137	1.912	1.038	(6.54)
High Book Leverage	1.576	1.369	2.024	2.467	1.361	(6.24)

Table 9: 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 *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.

	Data		Model	
	(1)	(2)	(3)	(4)
Constant	0.016	-0.030	0.018	0.013
	(4.33)	(-4.86)	(9.32)	(11.76)
Book Leverage	0.034	0.102	0.031	0.033
	(8.94)	(10.46)	(11.35)	(10.93)
Q	-0.009	0.007	-0.005	-0.004
	(-8.62)	(4.02)	(-6.92)	(-8.37)
Q $\times$ Book Leverage		-0.046		-0.001
		(-8.79)		(-4.18)
Time Fixed Effects	X	X	X	X
Industry Fixed Effects	X	X		
Clustered SE	X	X		
Observations	2007	2007	149053	149053
Adjusted-R^2	0.444	0.505	0.755	0.761

Table 10: 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.

	Panel A: Data					
	Market to Book Ratio					
	Low	(2)	(3)	High	H – L	t-stat
Low Book Leverage	1.215	0.788	0.691	0.510	-0.706	(-2.06)
(2)	1.635	1.026	0.739	0.519	-1.116	(-2.93)
(3)	1.766	1.234	0.959	0.652	-1.114	(-2.75)
High Book Leverage	4.068	2.450	1.404	0.668	-3.400	(-3.46)
	Panel B: Model					
	Market to Book Ratio					
	Low	(2)	(3)	High	H – L	t-stat
Low Book Leverage	0.901	0.679	0.586	0.505	-0.399	(-5.44)
(2)	1.551	0.913	0.707	0.603	-1.074	(-6.90)
(3)	2.201	1.279	0.925	0.748	-1.453	(-8.38)
High Book Leverage	2.964	2.288	1.905	1.807	-1.112	(-7.47)

Table 11: CDS and market–to–book — sensitivity analysis

This table presents regressions of CDS spreads on leverage and market–to–book ratios in simulated samples. Each regression has the same specification as column 3 of Table 9. Each simulated sample is obtained by simulating the model keeping the set of estimated parameters reported in Table 2, but perturbing the autocorrelation of the idiosyncratic shock (ρ_z) and the production function parameter (α) in the interval $[-0.05, 0.05]$ around the respective values reported in Table 2, $\hat{\rho}_z = 0.630$ and $\hat{\alpha} = 0.826$. Because changing the optimal parameters produces more skewed samples, we standardize all variables before estimation. Each reported coefficient represents the credit spread change, expressed in portion of a standard deviation, that corresponds to a one standard deviation change in the left hand side variable. We also report a coefficient t-statistics as well as the t-statistic of a test on the difference between the estimated regression coefficients on Q obtained from the original sample and those obtained from the perturbed samples.

Idiosyncratic shock autocorrelation parameter	$\hat{\rho}_z - 0.05$	$\hat{\rho}_z - 0.02$	$\hat{\rho}_z - 0.01$	$\hat{\rho}_z$	$\hat{\rho}_z + 0.01$	$\hat{\rho}_z + 0.02$	$\hat{\rho}_z + 0.05$
Book Leverage	1.281	1.353	1.366	1.391	1.443	1.460	1.422
	(77.50)	(72.11)	(70.71)	(66.49)	(64.18)	(61.60)	(59.84)
Q	-0.666	-0.774	-0.778	-0.842	-0.849	-0.885	-0.895
	(-75.45)	(-70.06)	(-65.76)	(-71.09)	(-56.09)	(-57.04)	(-69.23)
t-stat difference in Q parameter	(-50.48)	(-21.05)	(-23.71)		(2.01)	(10.44)	(13.76)
std(CDS)	0.007	0.007	0.007	0.007	0.007	0.007	0.007
std(Book Leverage)	0.335	0.352	0.390	0.394	0.436	0.444	0.469
std(Q)	1.265	1.490	1.638	1.773	1.857	2.005	2.474
Production function parameter	$\hat{\alpha} - 0.05$	$\hat{\alpha} - 0.02$	$\hat{\alpha} - 0.01$	$\hat{\alpha}$	$\hat{\alpha} + 0.01$	$\hat{\alpha} + 0.02$	$\hat{\alpha} + 0.05$
Book Leverage	1.344	1.384	1.403	1.352	1.338	1.303	1.231
	(74.99)	(72.28)	(66.41)	(71.72)	(74.46)	(88.30)	(79.42)
Q	-0.824	-0.814	-0.813	-0.787	-0.706	-0.648	-0.518
	(-74.70)	(-64.22)	(-57.06)	(-76.02)	(-67.53)	(-82.57)	(-88.71)
t-stat difference in parameter	(9.72)	(6.43)	(7.03)		(-26.56)	(-46.57)	(-60.44)
std(CDS)	0.007	0.007	0.007	0.007	0.007	0.007	0.007
std(Book Leverage)	0.404	0.407	0.410	0.372	0.390	0.361	0.342
std(Q)	1.806	1.725	1.713	1.672	1.603	1.573	1.443

Table 12: 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.

	(1)	(2)	(3)	(4)	(5)
Constant	0.020	0.006	0.016	0.018	0.026
	(9.09)	(7.06)	(7.82)	(9.20)	(8.78)
Leverage	0.016	0.038	0.034	0.030	
	(9.05)	(12.75)	(13.40)	(11.51)	
PVAP	-0.006		-0.004		-0.011
	(-6.80)		(-5.61)		(-5.69)
PVGO		-0.007	-0.006		-0.001
		(-7.22)	(-7.92)		(-2.16)
Q				-0.005	0.004
				(-6.81)	(4.12)
Time Fixed Effects	X	X	X	X	X
Observations	149053	149053	149053	149053	149053
Adjusted-R^2	0.678	0.725	0.768	0.755	0.538

Table 13: 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.

	Data			Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.017	0.075	0.073	0.017	0.024	0.023
	(4.65)	(9.23)	(8.98)	(8.21)	(5.97)	(5.95)
Book Leverage	0.038			0.030		
	(8.76)			(11.02)		
Q	-0.010	-0.010	-0.009	-0.005	-0.002	-0.002
	(-8.43)	(-8.67)	(-7.55)	(-6.42)	(-2.81)	(-2.76)
Current Asset		-0.011	-0.020		-0.005	-0.007
		(-8.16)	(-5.39)		(-5.89)	(-6.97)
Current Debt		0.007	0.007		0.009	0.014
		(5.85)	(4.43)		(8.68)	(8.50)
Lag Asset			0.009			0.003
			(2.59)			(9.88)
Lag Debt			-0.000			-0.005
			(-0.19)			(-7.38)
Time Fixed Effects	X	X	X	X	X	X
Industry Fixed Effects	X	X	X			
Clustered SE	X	X	X			
Observations	1822	1822	1566	134107	134107	133495
Adjusted-R^2	0.429	0.405	0.451	0.756	0.480	0.497

Table 14: 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.

	Data		Model	
	(1)	(2)	(3)	(4)
Constant	-0.001	-0.002	-0.001	-0.001
	(-0.45)	(-1.42)	(-0.68)	(-0.73)
Change in Book Leverage	0.023		0.019	
	(2.83)		(8.72)	
Profitability	-0.004	-0.001	-0.000	-0.001
	(-0.93)	(-0.17)	(-1.28)	(-3.10)
Change in Debt		0.005		-0.002
		(2.98)		(-4.82)
Investment		-0.004		-0.003
		(-2.33)		(-9.53)
Disinvestment		0.031		0.056
		(2.95)		(13.82)
Time Fixed Effects	X	X	X	X
Industry Fixed Effects	X	X		
Clustered SE	X	X		
Observations	1184	1184	131386	131386
Adjusted-R^2	0.363	0.365	0.347	0.350