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1-2012

## The Expected Cost of Default

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## The Expected Cost of Default\*

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January 2012

#### Abstract

The sample of observed defaults significantly understates the average firm's true expected cost of default due to a sample selection bias. To quantify this selection bias, I use a dynamic capital structure model to estimate firm-specific expected default costs. The average firm expects to lose 45% of firm value in default, a cost higher than existing estimates. However, the average cost among defaulted firms in the estimated model is only 25%, a value consistent with existing empirical estimates from observed defaults. This substantial selection bias helps to reconcile the levels of leverage and default costs observed in the data.

<sup>\*</sup>I am indebted to my dissertation committee, João Gomes, Ivan Shaliastovich, and Amir Yaron (Chair), for many helpful discussions, guidance, and support. Also, I thank Andy Abel, Franklin Allen, Hui Chen, Max Croce, Sergei Davydenko, Vincent Glode, Itay Goldstein, Todd Gormley, Mark Jenkins, Andrew Karolyi, Lars Kuehn, Oliver Levine, Anthony Lynch, David Ng, Christian Opp, Krishna Ramaswamy, Scott Richard, Michael Roberts, Nick Roussanov, Pavel Savor, Gustav Sigurdsson, Nick Souleles, Luke Taylor, Yu Yuan, and seminar participants at Wharton, Boston College (Carroll), Cornell (Johnson), Harvard Business School, Carnegie Mellon (Tepper), Dartmouth (Tuck), Duke (Fuqua), USC (Marshall), UCLA (Anderson), Chicago (Booth), London Business School, UNC (Kenan-Flagler), and the 2011 WFA meetings. Financial support from the Robert R. Nathan Fellowship is gratefully acknowledged. All errors are my own. The current version of the paper can be found at http://www.andrew.cmu.edu/user/gloverb

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## 1 Introduction

The cost of default is an essential component to understanding the joint behavior of default rates, credit spreads, and firms' optimal financing decisions. A common view in the finance literature, supported by empirical studies of defaulted firms, maintains that the average firm's cost of default is relatively low.<sup>1</sup> This conclusion plays a central role in the challenge faced by existing models to simultaneously explain the levels of leverage, credit spreads, and default rates observed in the data.

In this paper I show that estimates of default costs drawn from the sample of defaulted firms are subject to a substantial selection bias. Consequently, existing estimates of default costs significantly understate the cost that the average firm expects to incur in default. I find that using only a subset of defaulted firms gives an average default cost of 25% of firm value when, in fact, the average estimated cost for all firms in my sample is 45%.

This selection bias results from firms and credit markets internalizing default costs when choosing leverage and pricing debt, respectively. All else equal, firms with a higher cost of default will choose a lower level of leverage, making default less likely. Therefore, the firms that default ex post are disproportionately those with a low cost of default. This results in a selection bias that understates the cost of default.

I develop a structural model to estimate firm-specific expected default costs, which are the costs used ex ante by firms in setting their leverage and credit markets in pricing debt. Specifically, I embed a dynamic capital structure model in an economy with firm-level ex ante heterogeneity and time-varying macroeconomic conditions.<sup>2</sup> The model economy features a cross-section of firms that differ in their cost of default as well as the parameters of their cash flow process. Firms' optimal leverage, default decisions, credit spreads, and equity prices are

<sup>&</sup>lt;sup>1</sup>Andrade and Kaplan (1998) estimate the costs of financial distress to be 10-23% of the pre-distress firm value. This measure is intended to capture both direct and indirect costs. Estimates of direct bankruptcy costs are much smaller. Warner (1977), Weiss (1990), and Altman (1984) all find small direct costs of bankruptcy of 5.3%, 3.1%, and 6% of pre-bankruptcy firm value, respectively.

<sup>&</sup>lt;sup>2</sup>The structure of the model is similar to recent work by Bhamra, Kuehn, and Strebulaev (2010a,b), Chen (2010), and Hackbarth, Miao, and Morellec (2006). These papers feature contingent claims models of capital structure, in the spirit of Merton (1974) and Leland (1994), in environments with macroeconomic risk and show such risk is important for explaining levels of leverage and credit spreads.

all jointly determined endogenously in the model.

Using the structural model's implications for observable moments, I estimate firm-specific, unobservable expected default costs and cash flow parameters for a sample of approximately 2,500 U.S. firms. For each firm, the expected cost of default is estimated jointly with the three firm-specific cash flow parameters. Since all of these parameters, not just a firm's cost of default, affect its optimal leverage and default probability, allowing for firm-level heterogeneity in the cash flow parameters is important. In particular, it ensures that the distribution of implied default costs estimated from the model is not simply an inversion of the distribution of leverage. This can be seen by the fact that the estimates reveal a rich correlation structure in the firm-level cash flow and default cost parameters. Additionally, I investigate how the estimated default costs vary by industry and credit rating and how these costs correlate with firm characteristics that are not used in the estimation.

I then use the firm-specific estimates to quantify the selection bias in default costs. By simulating the estimated model and comparing the estimated default costs for the simulated defaults to the entire sample, I obtain an estimate of the selection bias. I find that existing estimates of default costs, based on a small sample of defaulted firms, are subject to a significant sample selection bias and, as a result, substantially understate the magnitude of expected default costs faced by most firms.

In my sample of 2,500 U.S. public firms, the mean estimated cost of default is 45% of firm value (with a median of 37%), which is substantially higher than existing estimates obtained from the empirical sample of defaulted firms. However, this value does not have a direct empirical counterpart and, given the selection bias, one should expect this value to be larger than what is obtained from a sample of defaulted firms. The striking result is that the estimated model produces an average default cost for the subset of defaulted firms of only 25%. This value, which is the model counterpart to the empirical sample of defaulted firms, is significant for two reasons. First, it implies a large selection bias — the average firm expects a cost of default nearly twice as large as the average inferred from the sample of defaulted firms. Second, and perhaps more importantly, this value is closely in line with

existing estimates of average default costs from the empirical sample of defaulted firms.<sup>3</sup>

A number of existing conclusions relating to leverage, credit spreads, and the importance of default costs rely on the assumption that the low observed default costs accurately reflect the costs faced by the broader population of firms. A central message of this paper is that many of these conclusions should be revisited. In particular, I show that accounting for heterogeneous default costs, and the sample selection bias that they induce, goes a long way towards resolving the underleverage puzzle. In addition, the sample selection bias has significant implications for a wide class of credit risk models, not just the framework used in this paper.

Using the values for default costs reported in Andrade and Kaplan (1998) and tax benefits to debt estimated by Graham (2000), previous work has concluded that default costs are too low for a tradeoff model of leverage to explain the low levels of leverage seen for many firms in the data. I show that, due to the sample selection bias, low observed default costs can be reconciled with low observed leverage ratios in a tradeoff model of leverage. The estimated model is not only consistent with observed default rates and credit spreads, but is also able to match the cross-section of leverage, including firms with very low leverage, while still replicating the low observed default costs seen in the data.<sup>4</sup>

In a broad sense, my work is related to a growing body of literature that considers the interactions of corporate financing decisions and asset prices. My approach to estimating firm-specific default costs and cash flow parameters is related to other recent papers estimating structural models.<sup>5</sup> A novel aspect of this paper is that I am able to estimate firm-specific parameters. In contrast, most related work estimates the parameters of a single

<sup>&</sup>lt;sup>3</sup>Andrade and Kaplan (1998), a frequently cited set of estimates in the literature, find average costs of 10-23% for a sample of 31 highly leveraged transactions that became distressed. Given that the sample selection problem is especially severe for such a sample and I look at all simulated defaults, not just a subset analogous to their HLTs, a value of 25% seems to be closely in line with their estimates. Furthermore, Andrade and Kaplan (1998) note this, saying "It is possible that the firms that undertook HLTs were those that, ex ante, expected to have low costs of financial distress. If this is true, our estimates of the costs of financial distress understate the costs of financial distress for firms in general" (p. 1489).

<sup>&</sup>lt;sup>4</sup>The model does not explain zero leverage firms, however, as this would likely require a fixed cost of initial debt issuance, which is excluded from the model for tractability.

<sup>&</sup>lt;sup>5</sup>Recent examples include Hennessy and Whited (2007), Morellec, Nikolov, and Schuerhoff (2010), and Nikolov and Whited (2010).

representative firm.

More specifically, my work is related to a strand of empirical literature that seeks to measure the cost of distress or default. The existing literature has generally found the average default costs observed in the data to be relatively low. Andrade and Kaplan (1998) estimate distress costs of 10-23% of firm value for a sample of 31 highly leveraged transactions. Davydenko, Strebulaev, and Zhao (2012) estimate an average default cost of 21.7% of the market value of assets from a sample of 175 defaulted firms. Using a natural experiment resulting from asbestos litigation, Taillard (2010) isolates financial from economic distress and finds little of evidence of significant costs of financial distress.<sup>6</sup>

The relatively small average default costs observed in the data has led to the conclusion that many firms are too conservative in their choice of leverage. Miller (1977) notes that default and distress costs appear far too small, given estimated tax benefits to debt, to explain empirical leverage ratios. Graham (2000) estimates the tax benefits of debt to up to 5% of firm value and concludes that from a tradeoff model of leverage many firms appear, on average, under levered.

Almeida and Philippon (2007) note that default is more likely to occur in bad states when marginal utility is high. Using risk-neutral probabilities and the estimates of Andrade and Kaplan (1998), they conclude that firms are not, on average, under levered. Elkamhi, Ericsson, and Parsons (2010) note that this calculation does not filter out economic shocks, which are unrelated to leverage, that drive the firm to default or distress. They argue that once the economic shocks are accounted for separately, the default cost estimates of Andrade and Kaplan (1998) are too low to account for the observed leverage ratios. The structural model that I use avoids this issue.

Using the marginal tax benefit estimates of Graham (2000), van Binsbergen, Graham, and Yang (2010) estimate firm-specific costs of debt under the assumption that firms are optimally levered. Based on the estimates of Almeida and Philippon (2007), they conclude

<sup>&</sup>lt;sup>6</sup>Additional examples of work studying distress or default costs include Pulvino (1998), Franks and Torous (1989), Opler and Titman (1994), Gilson (1997), Ofek (1993), Asquith, Gertner, and Scharfstein (1994), Bris, Welch, and Zhu (2006), and Acharya, Bharath, and Srinivasan (2007).

that approximately half of their estimated cost of debt is due to default or distress costs. My results suggest that, due to the sample selection bias, default or distress costs may represent a larger component of the cost of debt estimated by van Binsbergen, Graham, and Yang (2010).

Korteweg (2010) estimates the net benefits to leverage and, consistent with previous work, concludes that many firms are under levered. Using firms at or near distress, he estimates distress costs of 15-30%. These firms at or near distress, however, are likely to be those for which default costs were relatively low. George and Hwang (2010) also note that firms with high distress costs can be expected to choose low leverage to avoid distress. They argue that this provides an explanation for the distress risk and leverage puzzles observed in equity returns.

The model that I estimate is based on a class of structural models of capital structure and credit risk that build upon the seminal papers of Merton (1974) and Leland (1994). Specifically, the model in this paper is close to the models of Chen (2010), Bhamra, Kuehn, and Strebulaev (2010a,b), and Hackbarth, Miao, and Morellec (2006). These models are primarily concerned with matching aggregate facts regarding credit spreads, default frequency, and leverage. Chen (2010) seeks to explain the observed credit spreads and leverage ratios while Bhamra, Kuehn, and Strebulaev (2010b) focus on a levered equity premium. Bhamra, Kuehn, and Strebulaev (2010a) focus on the dynamics of leverage in an economy with macroeconomic risk. In their model, all firms are identical ex ante, but differ ex post due to idiosyncratic shocks. In contrast, I focus on computing a firm-specific measure of the cost of default and quantifying the magnitude of the sample selection bias. To that end, the economy I consider features a cross-section of firms which are ex ante heterogeneous, differing in the parameters of their cash flow process as well as default costs.

The remainder of the paper is organized as follows. In Section 2 I introduce the model framework and Section 3 discusses the implications of heterogeneity in default costs. In Section 4 I present simulation results from a calibrated version of the model in which firms

<sup>&</sup>lt;sup>7</sup>Other similar models include Chen, Collin-Dufresne, and Goldstein (2009), Fischer, Heinkel, and Zechner (1989), Goldstein, Ju, and Leland (2001)

differ ex ante only in their cost of default. I illustrate how the model is able to produce a counterfactual underleverage puzzle when, in fact, all firms are optimally levered. In Section 5 I estimate firm-specific expected default costs and cash flow parameters from the model. Section 6 examines how these firm-specific estimates relate to firm characteristics, industry, and credit rating. In Section 7 I simulate the model again under the estimated joint cross-sectional distribution of the firm-specific parameters, which gives an estimate for the sample selection bias in observed default costs. Section 8 concludes.

## 2 Model

I construct a partial equilibrium model featuring a cross-section of ex ante heterogeneous firms and time-varying macroeconomic conditions. The model setup is similar to the models of Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010a,b), with a key difference being that I allow for ex ante heterogeneity in multiple dimensions at the firm level.<sup>8</sup>

Specifically, I use a structural tradeoff model of the firm's dynamic capital structure decision in which the cash flows are specified exogenously. Firms are exposed to both systematic and idiosyncratic cash flow shocks in an environment with time-varying macroeconomic risk. Firms choose leverage ratios by weighing the tax benefits of debt against the deadweight losses incurred in default. Leverage, credit spreads, and firms' optimal default decisions are determined endogenously in the model with equityholders choosing optimal leverage to maximize firm value. Conditional on not defaulting, a firm can restructure upwards by issuing additional debt at any point in time. Restructuring is assumed to entail a cost, however, which results in firms choosing to restructure only once their cash flows exceed an optimally chosen restructuring boundary. In trading off the benefits of a tax shield with the costs of

<sup>&</sup>lt;sup>8</sup>These papers show that by introducing macroeconomic risk and a countercyclical price of risk, a dynamic tradeoff model of capital structure is able to match the observed average levels of leverage and credit spreads. Hackbarth, Miao, and Morellec (2006) and Chen, Collin-Dufresne, and Goldstein (2009) also consider timevarying macroeconomic conditions in models of credit risk, though in slightly different frameworks than the one used in this paper.

<sup>&</sup>lt;sup>9</sup>The option to restructure downwards is excluded for tractability. While perhaps limiting, this assumption is common to other dynamic capital structure models, such as, Goldstein, Ju, and Leland (2001), Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010a,b).

default, the model gives optimal leverage choices endogenously.<sup>10</sup>

Time is continuous and firms' investment policies are fixed. The state of the economy is determined by the state variable  $\nu_t$ , which evolves according to a 2-state time-homogeneous Markov chain. That is,  $\nu_t \in \{H, L\}$ , where the switching between regimes follows a Poisson arrival process. Changes in the aggregate state are assumed to be observable by all agents in the economy and given  $\nu_t$  the state-dependent parameters are known constants.

The aggregate earnings of the economy, denoted by  $X_{A,t}$ , evolve according to a Markov-modulated geometric Brownian motion:

$$\frac{dX_{A,t}}{X_{A,t}} = \mu_A(\nu_t)dt + \sigma_A(\nu_t)dW_t^A \tag{1}$$

where  $W_t^A$  is a standard Brownian motion. As indicated by the notation, the expected growth rate,  $\mu_A(\nu_t)$ , and volatility,  $\sigma_A(\nu_t)$ , of aggregate earnings depend on the aggregate state of the economy,  $\nu_t$ .

In the model, a firm's earnings growth depends on aggregate earnings shocks as well as idiosyncratic shocks specific to the firm. Firms' earnings are taxed at rate  $\tau_c$  and full loss offset is assumed. Firm i's before-tax earnings,  $X_{i,t}$ , evolve according to<sup>11</sup>

$$\frac{dX_{i,t}}{X_{i,t}} = (\mu_i + \mu_A(\nu_t))dt + \beta_i \sigma_A(\nu_t)dW_t^A + \sigma_{i,F}dW_t^{i,F}$$
(2)

This implies that firm i's expected earnings growth in state  $\nu_t$  is given by  $(\mu_i + \mu_A(\nu_t))$ , where  $\mu_i$  represents a state-invariant, firm-specific component and  $\mu_A(\nu_t)$  is the state-dependent expected growth rate of aggregate earnings. Thus, the expected earnings growth rate for all firms is assumed to depend, in part, on the aggregate state of the economy. Additionally,  $\beta_i$  parameterizes firm i's exposure to the aggregate earnings shocks generated by the Brownian motion  $W_t^A$ . Note that the volatility of aggregate earnings shocks,  $\sigma_A(\nu_t)$ , is assumed to be state-dependent, but a firm's exposure to these shocks,  $\beta_i$ , is constant. Finally, firm i is

<sup>&</sup>lt;sup>10</sup>Note, however, that due to fluctuations in firm cash flows and economic conditions and the assumed cost of restructuring, the firm's actual leverage will drift away from its optimal target. In the model, the firm is at its optimally chosen leverage ratio only at time 0 and subsequent restructuring dates.

<sup>&</sup>lt;sup>11</sup>I use the terms "earnings" and "cash flows" interchangeably. Both are meant to refer to the firm's earnings before interest and taxes.

exposed to idiosyncratic earnings shocks with volatility  $\sigma_{i,F}$  generated by the firm-specific Brownian motion  $W_t^{i,F}$ . By assumption,  $W_t^{i,F}$  is independent of  $W_t^A$  for all firms i. Thus, firms are exposed to three types of shocks: aggregate earnings shocks generated by  $W_t^A$ , idiosyncratic earnings shocks generated by  $W_t^{i,F}$ , and changes in the aggregate state of the economy,  $\nu_t$ .

### 2.1 Pricing Kernel, Risk Neutral Measure

I assume markets are complete and that there exists a default-risk-free asset that pays a state-dependent interest rate,  $r(\nu_t)$ . The model is partial equilibrium and I take the pricing kernel as exogenous. Specifically, the pricing kernel is assumed to evolve according to

$$\frac{d\pi_t}{\pi_t} = -r(\nu_t)dt - \varphi(\nu_t)dW_t^A. \tag{3}$$

In this economy,  $\varphi(\nu_t)$  is the state-dependent market Sharpe ratio and the risk premium for firm i's cash flows in state  $\nu_t$  is given by  $\beta_i \sigma_A(\nu_t) \varphi(\nu_t)$ . Given the specification for the pricing kernel, I can derive the risk-neutral probability measure,  $\mathcal{Q}$ , which will be used for pricing assets.<sup>12</sup> Under the risk-neutral measure, firm i's cash flow process evolves according to

$$\frac{dX_{i,t}}{X_{i,t}} = \widehat{\mu}_i(\nu_t)dt + \sigma_{i,X}(\nu_t)d\widehat{W}_t^i.$$
(4)

where  $\widehat{\mu}_i(\nu_t)$  represents the cash flow growth under the risk-neutral measure,  $\widehat{W}_t^i$  is a  $\mathcal{Q}$ -Brownian motion, and

$$\sigma_{i,X}(\nu_t) = \sqrt{(\beta_i \sigma_A(\nu_t))^2 + (\sigma_{i,F})^2}.$$

represents the total earnings volatility for firm i.

#### 2.2 Unlevered Firm Value

The unlevered value of the firm is the value if the firm were to never issue any debt, which is simply the value of a claim to the firm's perpetual cash flow stream.<sup>13</sup> The firm's earnings

<sup>&</sup>lt;sup>12</sup>Details of the derivation of the risk-neutral measure and risk-neutral cash flow dynamics are provided in Appendix A.

<sup>&</sup>lt;sup>13</sup>Details of the derivation of unlevered firm value are provided in Appendix B.

are taxed at rate  $\tau_c$  and full loss offset is assumed. At time t in state  $\nu_t$ , the value before taxes of unlevered firm i is given by

$$V_i^U(X_{it}, \nu_t) = E_t \left[ \int_t^\infty \frac{\pi_s}{\pi_t} X_{i,s} \, ds \, \middle| \, \nu_t \right]$$
 (5)

That is, the value of the unlevered firm is simply a claim to its perpetual stream of cash flows. Note that this value is state-conditional but time-independent. Alternatively, the before-tax unlevered value of firm i in state  $\nu_t$  at time t can be expressed as

$$V_i^U(X_{i,t}, \nu_t) = \frac{X_{i,t}}{r_i^U(\nu_t)}$$
 (6)

where  $r_i^U(\nu_t)$  is the discount rate applied to firm i's unlevered cash flows in state  $\nu_t$ . For current state H,

$$r_i^U(H) = \frac{[\lambda_{HL} + r^f(H) - \widehat{\mu}_i(H)][\lambda_{LH} + r^f(L) - \widehat{\mu}_i(L)] - \lambda_{HL}\lambda_{LH}}{r^f(L) - \widehat{\mu}_i(L) + \lambda_{HL} + \lambda_{LH}}$$
(7)

where  $r^f(H)$  is the instantaneous risk-free rate in state H,  $\hat{\mu}_i(H)$  is firm i's risk-neutral cash flow growth rate in state H, and  $\lambda_{HL}$  is the probability of switching from state H to L. This expression shows that the discount rate applied to the firm's cash flows accounts for the possibility of a change in the aggregate state. An analogous expression holds for  $r_i^U(L)$ . With no regime-switching, the expression for unlevered firm value collapses to a familiar Gordon growth formula:

$$V_i^U(X_{i,t}, \nu_t) = \frac{X_{i,t}}{r^f - \widehat{\mu}_i}.$$

The value in state  $\nu_t$  of a consol bond,  $b(\nu_t)$ , that has no default risk and pays a constant coupon rate of 1 can be computed similarly and is given by

$$b(\nu_t) = \frac{1}{r^P(\nu_t)} \tag{8}$$

where  $r^P(\nu_t)$ , is the interest rate in state  $\nu_t$  on a default-risk-free perpetuity. For current state H,

$$r^{P}(H) = r^{f}(H) + \frac{\lambda_{HL}(r^{f}(L) - r^{f}(H))}{\lambda_{HL} + \lambda_{LH} + r^{f}(L)}.$$

with an analogous expression holding for  $r^{P}(L)$ .

### 2.3 Financing Decision

Firms make their leverage and default decisions by balancing the benefit of the interest tax shield against the cost of default, with the objective of maximizing the value of equity. Firm i issues debt in the form of a perpetuity that pays a constant coupon rate of  $C_i$ . This rate is chosen at issuance and paid to bondholders until equityholders choose to default or restructure by issuing additional debt. In the case of restructuring, a firm calls its outstanding debt and issues a new perpetuity with a new coupon rate.

The firm is assumed to distribute all earnings after the coupon payment and corporate taxes to equity holders in the form of a dividend, which is taxed at rate  $\tau_d$ . In the event that current earnings are less than the coupon payment owed,  $X_{i,t} - C_i < 0$ , the firm can issue additional equity. Due to limited liability, equity holders are not obligated to inject additional funds to pay the bondholders. However, failure to do so results in default at which point the bondholders receive ownership rights to the firm. Consequently, equity holders will optimally choose to raise additional funds only in the event that the value of equity in the current state is positive. Thus, under the assumption that the absolute priority rule holds, equityholders optimally choose to default once the equity value is 0.

#### 2.4 Default Event and the Cost of Default

In the event of default, debtholders take over the firm with equityholders receiving nothing. Firms incur a cost in the event of default, which reduces debtholders' recovery rate. In particular, if firm i defaults at time t, bondholders receive  $(1-\alpha_i)V_i^U(X_t,\nu_t)$  where  $V_i^U(X_t,\nu_t)$  is the unlevered value of firm i given in equation (6). Thus,  $\alpha_i$  represents the fraction of firm i's unlevered value that is lost in the event of default. As indicated by the notation, these costs are assumed to vary across firms but are constant across aggregate states.<sup>14</sup> While

<sup>&</sup>lt;sup>14</sup>The model readily allows for state dependence in  $\alpha_i$  and there is empirical evidence that recovery rates vary with economic conditions, which would motivate such a feature. For the results presented, I choose to shut down state-dependence in  $\alpha$  to be consistent with the estimation in Section 5. Because I do not have sufficiently rich data to identify firm-specific time variation in  $\alpha_i$ , the estimation requires this parameter to be fixed through time. Therefore, to present simulation results consistent with the model that I estimate, I set  $\alpha_i(\nu_t) = \alpha_i$ .

I do not specifically model the nature of this loss, it may be due to a variety of factors such as reputation costs, asset fire sales, loss of customer or supplier relationships, legal and accounting fees, and costs of changing management.

#### 2.5 Overview of the Firm's Problem

In order to solve for a firm's optimal capital structure, the values of debt and equity must first be computed. Given the specified cash flow process and pricing kernel, I use a contingent claims approach to solve for the values of these securities and then find the optimal coupon that maximizes initial firm value for each firm. The solution procedure is as follows. First, I solve for the unlevered value of the firm. Then, I solve for the values of debt and equity for arbitrary coupon rate and set of restructuring thresholds with the optimally chosen default thresholds determined by the smooth-pasting conditions. Given these security values, I solve for the optimal default thresholds chosen by the equity holders as a function of an arbitrary coupon. Finally, I solve for the optimal coupon rate and set of upward restructuring thresholds subject to the smooth pasting conditions for the default thresholds.

## 2.6 Valuing Debt and Equity

Debt and equity are contingent claims on a firm's cash flows that pay a continuous dividend rate while the firm is solvent and a lump sum payment in the event of default. As time-homogeneous contingent claims, the values of these two securities at time t depend only on the present cash flows,  $X_{i,t}$ , and the current state,  $\nu_t$ . Thus, the debt and equity values can be solved for in a manner analogous to the technique used to solve for the unlevered firm value. In particular, the values for debt and equity can be characterized as systems of ordinary differential equations.

Once a firm has issued debt, default becomes a possibility and the firm must choose a cash flow threshold at which it defaults. Since the value of a firm's cash flows (as well as a contingent claim on the cash flows) is different in the two states, a firm will have a different

<sup>&</sup>lt;sup>15</sup>The solution technique follows that of Chen (2010), which is based on a method of pricing options on securities with Markov-modulated dynamics presented in Jobert and Rogers (2006).

default threshold for each state. I denote the threshold at which firm i defaults in state  $\nu_t$  as  $X_{D_i,\nu_t}$ . Since equity holders receive nothing in default, the default threshold for a given state will always be less than the coupon payment.

Debt is a contingent claim on firm i's cash flows that pays the constant coupon payment  $C_i$  while the firm is solvent and pays  $(1 - \alpha_i)V_i^U(X_{i,t}, \nu_t)$  in the event of default by firm i at time t in state  $\nu_t$ . That is, debt holders receive a fraction  $(1 - \alpha_i)$  of the unlevered firm value in the event of default, where the size of the fraction as well as the unlevered firm value depend on the state.

In what follows, I suppress the firm-specific subscript for notational convenience. The values presented apply to a given firm, but are not fixed to be constant across firms. In the event of restructuring, the debt is called and the bondholders receive  $D(X_0; \nu_0)$ . When default occurs at time t in state  $\nu_t$ , the bondholders receive a payment of  $(1 - \alpha)V(X_t, \nu_t)$ . For current cash flow  $X_t$ , debt issued when the state was  $\nu_0$  has current value given by

$$D(X_t; \nu_0) = \sum_{j=1}^k w_{k,j}^D(\nu_0) \mathbf{g}_{k,j} X_t^{\psi_{k,j}} + \xi_k^D(\nu_0) X_t + \zeta_k^D(\nu_0), \ X_t \in \mathcal{R}_k, \ k = 1, 2, 3$$
 (9)

where  $\mathcal{R}_k$  represents the current cash flow region. The  $\psi$ 's are the eigenvalues and g represent the eigenvectors of the firm's eigenvalue problem presented in the Appendix. The terms  $\xi_k^D(\nu_0)$  and  $\zeta_k^D(\nu_0)$  represent solutions to the inhomogeneous equation.

Similarly, equity is a contingent claim that pays a dividend  $(X_{i,t} - C_i)$  until default or restructuring occurs. In the event of restructuring, the equity holders have a claim to the newly levered firm value. As previously mentioned, in default, equity holders receive nothing. Thus, for current cash flow  $X_t$  and initial debt issuance occurring in state  $\nu_0$ , the value of equity is given by

$$E(X_t; \nu_0) = \sum_{j=1}^k w_{k,j}^E(\nu_0) \mathbf{g}_{k,j} X_t^{\psi_{k,j}} + \xi_k^E(\nu_0) X_t + \zeta_k^E(\nu_0), \quad X \in \mathcal{R}_k, \quad k = 1, 2, 3$$
 (10)

With these expressions, we can solve for the firm's optimal capital structure, which consists of choosing a coupon rate and default and restructuring boundaries.

#### 2.7 Firm's Problem

The firm faces a dynamic capital structure decision at time t=0. In choosing its capital structure, the firm balances the tax benefits of debt against the expected cost of default. The debt issued is a perpetuity and the firm is able to restructure upwards in the future by issuing additional debt, subject to a proportional cost of debt issuance,  $\phi_D$ . This proportional issuance cost is paid on the total amount of debt outstanding. As such, the firm faces effectively a fixed cost component on its current outstanding debt and consequently it chooses not to issue debt continuously. Instead, it will choose thresholds for the level of earnings at which point the firm finds it optimal to issue additional debt. Given the initial state,  $\nu_0$ , the firm chooses the coupon rate and two state-dependent default and upward restructuring boundaries,  $\{\mathbf{X}_{\mathbf{D}}(\nu_0), \mathbf{X}_{\mathbf{U}}(\nu_0)\}$ , to maximize the initial value of equity. At time 0, the initial value of the firm for initial cash flow level  $X_0$  and initial state  $\nu_0$  is given by

$$E(X_0, \nu_0; \nu_0) + (1 - \phi_D)D(X_0, \nu_0; \nu_0)$$
(11)

where  $\phi_D$  is a proportional cost of debt issuance. Note that even at a later date, t, the equity and debt value depend on the initial state,  $\nu_0$ , and well as the current state,  $\nu_t$ . Similarly, the coupon rate and thresholds chosen will depend on the initial state. The firm's problem is given by

$$\max_{\mathbf{C}(\nu_0), \mathbf{X}_{\mathbf{U}}(\nu_0)} E(X_0, \nu_0; \nu_0) + (1 - \phi_D) D(X_0, \nu_0; \nu_0) \quad s.t.$$

$$\frac{\partial}{\partial X} E(X, k, \mathbf{C}; \nu_0) \Big|_{X \downarrow X_D^k(\nu_0)} = 0, \quad k = 1, 2$$
(12)

where  $\mathbf{X}_{\mathbf{U}}(\nu_0) = \{X_U^1(\nu_0), X_U^2(\nu_0)\}.$ 

The initial optimal leverage ratio is given by

$$L_0(X_0, \nu_0) = \frac{D(X_0, \nu_0; C^*)}{E(X_0, \nu_0; C^*) + D(X_0, \nu_0; C^*)}$$
(13)

where  $C^*$  is the optimally chosen coupon rate.

#### 2.8 Comment on Distress and Default Costs

In the model, firms do not incur distress costs prior to declaring default, at which point the equity holders no longer have a claim to the firm. In reality, firms typically incur distress costs prior to the event of default and some firms may incur distress costs without ever declaring default. Moreover, the costs of distress outside of default are borne directly by equity holders (though debtholders may suffer losses as a result), whereas default in the model occurs when equity value is zero, with the subsequent default costs coming out of the bondholders' recovery.

Despite this simplification, the effect on a firm's capital structure decision is similar to a model with explicit distress costs. In the model, equityholders do not explicitly incur distress costs, but they behave as if they did insofar as the costs borne by the debtholders in default are internalized by the equityholders. In the model, a higher cost of default results in a lower recovery rate for debtholders, all else equal. Recognizing this, the debtholders demand a higher credit spread for a given level of leverage and default probability. This leads a firm with larger default costs to issue less debt and thus have a lower default probability than an otherwise identical firm with smaller default costs. While the default costs are not directly borne by the equityholders, they internalize these costs as they adjust their optimal level of leverage. Thus, even without explicit distress costs incurred prior to default, equityholders still behave similarly to a case with such explicit costs. This underscores the importance of using a modeling framework in which leverage choices and debt prices are determined jointly and endogenously. The equilibrium pricing of the firm's debt ensures that default costs, which are borne directly by debtholders, are internalized by the equityholders when choosing leverage.

## 3 Model Implications

As a starting point, I calibrate a model economy of ex ante heterogeneous firms to match both aggregate and cross-sectional features of the data. This allows me to examine the quantitative

impact of variation in default costs on a firm's optimal leverage decision, default probability, credit spread, and price of debt and equity. The model generally matches the salient features of the data and thus provides an environment in which the quantitative magnitude of the bias in default costs can be examined. Before discussing the model calibration and simulation results, I first present some comparative statics for optimal firm policies and credit spreads with respect to variation in a firm's default cost parameter,  $\alpha_i$ .

Figure 1 shows how variation in  $\alpha$  affects optimal firm policies, credit risk, and firm value. Each plot shows variation in  $\alpha$  between 0 and 1, fixing all other parameters at the values given in Table I. In all cases, the initial state is the high state and the initial cash flow,  $X_0$ , is normalized to 1. Panel A of Figure 1 displays a firm's optimal initial book leverage as a function of  $\alpha$ . As expected, optimal leverage is decreasing in the magnitude of default costs. Intuitively, higher default costs make a firm's cost of debt higher, while leaving the tax benefits unchanged, thus leading to a lower optimal leverage ratio.

Similarly, Panel C indicates that the optimal coupon is decreasing in a firm's default cost. That is, a firm with a higher cost of default optimally chooses to issue less debt. It is important to note that this is an optimal choice with respect to the objective of maximizing the initial total firm value. Since the firm is initially all equity, this is the same as saying the equityholders are maximizing the initial value of equity. Panel D shows that for a fixed level of earnings, the total firm value is decreasing in default costs. Issuing debt gives the firm a tax shield that increases its value. For a given face value, the debt of a firm with high default costs is worth less.

Panel B of Figure 1 shows the optimal default thresholds for each state as a function of default costs. The solid (dashed) line indicates the default threshold when the current state is high (low). As indicated by the graph, for all values of  $\alpha$ , firms choose to default sooner in the low state than in the high state. Under the parameter specification of Table I, the value of equity is higher in the high state. Additionally, Panel B shows that firms with low costs of default optimally choose to default sooner than those with high costs. As indicated by the plot, this relationship is nonlinear and indicates that in the model firms with low costs

of default are more likely to default, all else equal.

## 4 Simulation Results

In this section I simulate the model fixing all firm-specific parameters except for the default cost,  $\alpha$ , which is assumed to be distributed U[0,1] in the cross-section. This provides a benchmark environment in which the effects of heterogeneity in default costs can be studied, separate from heterogeneity in the other firm-specific parameters of the model. In Section 5, I jointly estimate the four firm-specific parameters for my sample of firms and in Section 7 I present results from the model simulated under the estimated parameter distribution. As will be shown in Section 5, there is nontrivial correlation structure in the estimated firm-specific parameters. Thus, I use this section to isolate the effect of heterogeneity in default costs and provide a sense of whether this heterogeneity alone can produce a significant selection bias.

#### 4.1 Parameter Calibration and Benchmark Results

To generate results from the model, I perform 5,000 simulations of a panel of 5,000 firms. The model is simulated at a quarterly frequency for 35 years and simulated sample statistics are averaged across the 5,000 simulations. In order to maintain a balanced panel in the simulation, I assume that a new, ex ante identical firm replaces a defaulting firm in the same period that default occurs. This means that the mass of firms as well as the cross-sectional parameter distribution is constant through each simulated time series.

To illustrate the effects of ex ante heterogeneity in default costs, distinct from variation in other firm specific parameters, in this section I only consider cross-sectional variation in  $\alpha$ . That is, all firm-specific parameters except for  $\alpha$  are identical across firms. However, firms are still exposed to idiosyncratic earnings shocks and therefore will differ ex post. Table I presents the parameter values used in the benchmark model calibration. I assume in the cross-section  $\alpha_i \sim U[0,1]$  and it is constant across states.<sup>16</sup> To implement this, I discretize

<sup>&</sup>lt;sup>16</sup>Empirically, there is evidence that recovery rates are lower in times of bad economic conditions, when there are a greater number of defaults. See, for example, Altman et al. (2005). To illustrate the effect of cross-sectional heterogeneity in  $\alpha$ , distinct from time variation, I do not allow  $\alpha$  to vary across economic

the distribution into 40 grid points for  $\alpha$ , each with equal mass and solve the model for each of these firm "types." In Section 5, I allow for firm-level heterogeneity in all four firm-specific parameters and estimate firm-specific parameters for each of the 2,505 firms in my sample. I now describe the calibration and estimation of the other model parameters used in this section.

First, I estimate the parameters of the regime-switching aggregate earnings process using quarterly aggregate earnings data from NIPA Table 1.14 provided by the BEA.<sup>17</sup> In the model, aggregate earnings is assumed to evolve according to a Markov-modulated geometric Brownian motion:

$$\frac{dX_t^A}{X_t^A} = \mu^A(\nu_t)dt + \sigma^A(\nu_t)dW_t^A. \tag{14}$$

By Itô's Lemma, the quarterly log earnings growth rate,  $x_{t+1}$ , can be written as

$$x_{t+1}^{A} \equiv \Delta log(X_{t+1}^{A}) = \mu^{A}(\nu_{t}) - \frac{1}{2}\sigma^{A}(\nu_{t}) + \varepsilon_{t+1}^{A}$$
(15)

where  $\varepsilon_{t+1}^A \sim \mathcal{N}(0, (\sigma^A(\nu_t))^2)$ . The identifying assumption for the two regimes is a negative earnings growth rate in the low state. I estimate the six parameters of the aggregate earnings process,  $\{\mu_1^A, \mu_2^A, \sigma_1^A, \sigma_2^A, \lambda_{12}, \lambda_{21}\}$ , via maximum likelihood. The estimates for the aggregate earnings process and the generator matrix,  $\Lambda$ , are presented in Table I. Note that the low state, which is identified by the negative earnings growth, also has higher volatility. For details on the estimation procedure, see Appendix F.

The tax rate on corporate profits is set to 35%, the current top U.S. federal corporate marginal tax rate. The tax rate on equity distributions,  $\tau_d$ , and interest income,  $\tau_i$ , are set to 12% and 29.6%, respectively, which are the values computed in Graham (2000). The cost of debt issuance,  $\phi_D$  is set to match the costs found in Altinkilic and Hansen (2000).

In this version of the simulation, all firms have identical cash flow parameters,  $\mu_i$ ,  $\beta_i$ , and  $\sigma_i^F$ . I set  $\mu_i = 0$  so that all firms have a state-conditional expected earnings growth equal to the aggregate. Idiosyncratic volatility,  $\sigma_i^F$ , is set to match the cross-sectional variance of earnings growth in the data.

states.

<sup>&</sup>lt;sup>17</sup>Additional details can be found in Appendix E.

In Table II I compare moments generated from the model simulations with their counterparts in the data. Additionally, at each date in the simulation, I assign each firm to a credit rating according to its expected default probability. In Table III, I compare the credit spreads and default probabilities for the ratings groups in the model with their empirical counterparts. As indicated by these tables, the model appears to succeed in matching several salient features of the data, particularly the average default rate, leverage, and credit spreads.

#### 4.2 Selection Bias in Default Costs

By simulating the model, I am able to compare the "true," unconditional distribution of  $\alpha$ , which I have specified, with the conditional distribution inferred from the sample of defaults in the simulated data. This allows me to quantify the magnitude of the bias in the estimated  $\alpha$ . I assume that the econometrician can only observe firm i's cost of default,  $\alpha_i$ , if the firm defaults. Thus, the econometrician can use the sample of historical defaults to construct a distribution of default costs from the firms that default. I denote the mean of this conditional distribution as  $\widehat{\alpha}_{\text{Default}}$ , which is defined as

$$\widehat{\alpha}_{\text{Default}} = \mathbb{E}[\alpha_i \mid \text{Firm } i \text{ Defaulted}] \tag{16}$$

I simulate the panel of 5,000 firms for 35 years and I repeat the simulation 5,000 times. For each simulation, I take the set of firms which defaulted during the 35 year period and compute the average  $\alpha$  of the firms in this sample. Thus, each simulation has a computed value of  $\widehat{\alpha}_{Default}$ .

In Figure 2, I plot a histogram of the 5,000  $\hat{\alpha}_{Default}$  values computed in each simulation. The vertical red dotted line represents the unconditional mean of the distribution of  $\alpha$ . As indicated by the figure, in every simulation  $\hat{\alpha}_{Default}$  is substantially smaller than the unconditional mean  $\alpha$  represented by the vertical dotted line. In this sense, the existence of the bias in  $\alpha$  is not a statement about a particular sample path observed in the data. The variation in the histogram shows that the magnitude of the bias varies across sample paths but in all simulations the bias is quantitatively large. Put differently, in any of the model

simulations the average cost of default inferred from the sample of defaulted firms is much smaller than the "true," unconditional average cost faced by all firms.

This bias does not just affect the estimated mean value of the default cost. Figure 3 plots the inferred and true distributions for  $\alpha$ . The inferred distribution is taken by averaging over all 5,000 simulations. As shown, low-default-cost firms are over-represented and those firms with a high cost are underrepresented in the sample of defaults. This leads one to infer a distribution for  $\alpha$  that is very different from its true distribution.

The intuition for this effect is straightforward. If two firms differ in their default costs, but not the tax benefits to issuing debt, then the firm for which default is more costly should endogenously choose a lower leverage ratio such that it is less likely to default. Firms trade off the expected benefits of the tax shield with the expected costs of default. A firm that incurs higher costs conditional on default reduces its expected costs by issuing less debt, thus making default less likely. This naturally results in firms with a lower cost of default having a higher default probability in equilibrium.

## 4.3 Underleverage

Having established that the model produces ex post estimates of default costs,  $\alpha$ , that are substantially smaller than the unconditional average, I now illustrate how this generates what appears to be an underleverage puzzle. Throughout this section, I use the parameters given in Table I.

In Panel C of Figure 1, I plot the interest coverage ratio at time 0 for firms that differ in their  $\alpha$ 's but are otherwise identical.<sup>18</sup> In the framework of Graham (2000), these firms have identical tax benefit functions with "kinks" at the same level of interest expense.<sup>19</sup> In that respect, the high  $\alpha$  firms, which optimally choose lower leverage, appear to be underlevered. That is, it seems that these firms could increase value by issuing additional debt.

Figure 4 plots the initial total firm value as a function of the default cost  $\alpha$ , again with

<sup>&</sup>lt;sup>18</sup>Since firms in the model issue perpetuities which pay no principal, the interest coverage coverage ratio, measure as the ratio of earnings to interest expense, is higher in the model than in the data.

<sup>&</sup>lt;sup>19</sup>Graham (2000) defines the "kink" in a firm's marginal tax benefit function as the point at which the function becomes downward sloping.

all other parameters fixed across firms. Note that the earnings process for all of these firms is identical. While earnings will differ ex post due to differences in the realizations of firm-specific shocks, all firms in Figure 4 have identical ex ante tax benefits to debt. These firms differ in their default costs, however, which leads them to optimally select different levels of leverage. Moreover, the figure shows that these differences in the default costs,  $\alpha$ , produce large differences in optimal leverage. Since the default costs,  $\alpha$ , are unobserved prior to default, these firms appear identical ex ante, with the exception of their chosen leverage ratio and credit spread.

Examining Figure 4, it appears that the lower leverage firms could increase their value by issuing more debt. However, this is not the case. Each firm has chosen its debt optimally to maximize the initial equity value. Thus, issuing more debt for any firm here would result in a reduction in value.<sup>20</sup> Thus, the unobserved heterogeneity in  $\alpha$  makes some firms appear to use debt too conservatively, when in fact this is not the case.

This does not rule out the possibility that there are firms in the data which are, in fact, underlevered. However, failure to account for the effects of heterogeneity in default costs has the effect of making the underleverage puzzle appear more severe than it is. Moreover, in the model I show that this effect is quantitatively large, and thus can potentially account for a significant portion of the underleverage puzzle observed in the data.

## 5 Model Estimation

In this section, I estimate firm-specific default costs and cash flow parameters using a simulated method of moments procedure. I construct a sample of firms from the Compustat Fundamentals Quarterly file merged with equity data from CRSP. Details and variable definitions are provided in Appendix E. The dataset consists of firm-specific moments for 2,505 firms. The aggregate parameters are set to the values calibrated in the model simulation of Section 4.

<sup>&</sup>lt;sup>20</sup>The comparisons here are made using time-0 values. The results do not depend on this, however, and the same conclusions would hold at a later time for firms which experience the same realization of shocks.

### 5.1 Estimation Overview

The method of moments estimator selects the vector of parameters for each firm that minimizes the distance between a firm's moments in the data and moments from simulated data produced by the model. Intuitively, it selects the set of model parameters for each firm that "best" explain that firm's data moments. Recall that in the model firm i's cash flows evolve according to

$$\frac{dX_{i,t}}{X_{i,t}} = (\mu_i + \beta_i \mu_A(\nu_t))dt + \beta_i \sigma_A(\nu_t)dW_t^A + \sigma_{i,F}dW_t^{i,F}$$
(17)

This gives three firm-specific cash flow parameters  $(\mu_i, \beta_i, \sigma_i^F)$ , in addition to the cost of default parameter,  $\alpha_i$ , to be estimated for each of the 2,505 firms in my sample. For each firm i in the sample, I estimate a firm-specific vector of parameters,  $\theta_i$ , where

$$\theta_i = [\alpha_i \quad \mu_i \quad \beta_i \quad \sigma_{i,F}]$$

Let  $M^i$  denote the  $K \times 1$  vector of data moments for firm i. Given a parameter vector  $\theta$ , for each simulation s = 1, ..., S, I simulate a time series of length T and compute a vector of moments from the simulated data,  $\widetilde{\mathcal{M}}_s(\theta)$ , that serves as an analog to the data moments,  $M^i$ . The method of moments estimator for the parameters of firm i is defined as

$$\widehat{\theta_i} = \underset{\theta}{\operatorname{argmin}} \left( M^i - \frac{1}{S} \sum_{s=1}^S \widetilde{\mathcal{M}}_s(\theta) \right)' W_i \left( M^i - \frac{1}{S} \sum_{s=1}^S \widetilde{\mathcal{M}}_s(\theta) \right)$$
(18)

where  $W_i$  is a positive semidefinite weighting matrix for firm i. Following Duffie and Singleton (1993), I choose  $W_i = \Sigma_{0,i}^{-1}$ , where

$$\Sigma_{0,i} = \sum_{j=-\infty}^{\infty} \mathbb{E}_t \left( [m_{i,t} - \mathbb{E}_t(m_{i,t})] [m_{i,t-j} - \mathbb{E}_t(m_{i,t-j})]' \right)$$
 (19)

with  $\Sigma_{0,i}$  approximated using the estimator of Newey and West (1987). Note that  $m_{i,t}$  is the observation at date t for firm i from the data, meaning  $\Sigma_{0,i}$  depends only on firm i's empirical data, not the simulated data. Define  $u_{i,t} = (m_{i,t} - \sum_{t=1}^{T_i} m_{i,t})$ , where  $T_i$  is the empirical sample length for firm i. I approximate the spectral density matrix for firm i using

$$\widehat{\Sigma}_{i} = \sum_{j=-k}^{k} \left( \frac{k - |j|}{k} \right) \frac{1}{T_{i}} \sum_{t=1}^{T_{i}} \left( u_{i,t} u'_{i,t-j} \right)$$
(20)

where I select k=2. Duffie and Singleton (1993) show that under the appropriate conditions,

$$\sqrt{T}(\widehat{\theta}_{T,i} - \theta_{0,i}) \to \mathcal{N}[0, (1 + 1/S)(H'_{0,i} \Sigma_{0,i}^{-1} H_{0,i})^{-1}]$$
(21)

where S denotes the number of simulations of length  $T_i$  and

$$H_{0,i} = E \left[ \frac{\partial \widetilde{\mathcal{M}}_s(\theta_{0,i})}{\partial \theta} \right]. \tag{22}$$

I repeat the SMM procedure for each firm in the sample, obtaining a  $1 \times 4$  vector of parameter estimates,  $\hat{\theta}_i$ , and standard errors for each firm i = 1, ..., N.

#### 5.2 Selection of Moments

The selection of moments used in the estimation is important to ensure that the four parameters are identified. I select a set of seven firm-specific moments that are informative in that they are sensitive to the parameter values. The set of moments chosen includes moments that are informative about both prices and quantities. Specifically, the moments used in the estimation are the firm's mean book leverage, mean excess equity return, mean price-earnings ratio, mean earnings growth rate, volatility of earnings growth, mean of quasi-market leverage, and volatility of quasi-market leverage. <sup>21</sup> I briefly discuss the moments identifying each of the parameters.

The cost of default parameter,  $\alpha_i$  is determined by the book and quasi-market leverage measures. As shown in Panel A of Figure 1, the firm's optimal leverage choice is sensitive to the value of default costs. Additionally, since quasi-market leverage contains the market value of equity, it contains information independent of book leverage. As a result, both are informative regarding the default cost parameter  $\alpha_i$ .

As one would expect, the firm-specific component to expected earnings growth,  $\mu_i$ , is pinned down primarily by the earnings growth rate, however, other moments are informative as well. The price-earnings ratio, for example, is increasing in the rate of earnings growth,

<sup>&</sup>lt;sup>21</sup>The quasi-market leverage measure is the ratio of the book value of debt to the sum of the book value of debt and market value of equity.

all else equal. Intuitively, controlling for the discount rate, a firm with a higher expected earnings growth has a larger value of equity and thus a higher price-earnings ratio.

The firm's risk exposure, which is parameterized by  $\beta_i$ , impacts the mean excess equity return, price-earnings ratio, and quasi-market leverage values. A larger value of  $\beta_i$  implies greater exposure to systematic risk, which translates to a higher expected return. Similarly, this higher expected return results in a lower present value of equity, which all else equal, means a lower price-earnings ratio. While an increase in  $\beta_i$  does increase the volatility of quasi-market leverage and earnings, the impact on these moments is substantially smaller. This is because most of the variation in the volatility measures is driven by differences in the idiosyncratic volatility, not differences in exposure to aggregate shocks. Additionally, an increase in  $\beta_i$  increases the mean quasi-market leverage ratio in that it reduces the market value of equity, all else equal. However, again, this affect is small compared to the impact of other parameters on the quasi-market leverage ratio.

Finally, the idiosyncratic volatility,  $\sigma_{i,F}$  is determined primarily by the earnings growth and quasi-market leverage volatilities. Again, this is straightforward as these volatility measures are monotonically increasing in  $\sigma_{i,F}$ . However, the volatility also impacts the levels of book and quasi-market leverage as a higher volatility, all else equal, implies a greater default probability. At the same time, this effect is somewhat mitigated by the fact that, all else equal, higher idiosyncratic volatility increases the equityholders' option to delay default.

#### 5.3 Estimation Results

The results from the estimation are presented in Figure 5, which shows the cross-sectional distribution for each of the four firm-specific parameters. Panel A of Figure 5 shows the cross-sectional distribution of the estimated default cost parameter,  $\alpha_i$ . Note that the estimated values of  $\alpha_i$  show considerable cross-sectional dispersion, with a standard deviation of 27%. This suggests that applying a single cost of default to the entire cross-section of firms is likely to give misleading results.

In Table IV, I present summary statistics and correlations for the estimated parameters.

As indicated in the first row of Panel A of the table, the mean estimated default cost in the sample of 2,505 firms is 44.5% of firm value, with a median value of 36.8%. Additionally, the estimated values of  $\alpha_i$  display significant heterogeneity with a cross-sectional standard deviation of 27%. The remaining rows of Panel A display statistics for the estimated firm-specific cash flow parameters. These parameters also display considerable cross-sectional standard deviation.

In Panel B of Table IV, I report the correlation matrix for the estimated firm-specific parameters for the 2,505 firms in my sample. It is interesting to note that the estimated default cost,  $\alpha$ , has nontrivial correlation with the estimated cash flow parameters. Specifically, the estimated default cost is negatively correlated with a firm's idiosyncratic volatility,  $\sigma_i^F$ , and positively correlated with its systematic risk exposure,  $\beta_i$ , and expected earnings growth,  $\mu_i$ . This correlation structure displayed in Panel B, along with the significant heterogeneity in the estimated cash flow parameters, underscores the importance of jointly estimating the firm-specific default cost and cash flow parameters. Finally, Panel C of Table IV displays Spearman rank correlations for the estimated parameters and data moments.

For each firm i in my sample of 2,505 firms, I estimate a  $4 \times 1$  vector,  $\theta_i$ , of the firm-specific parameters. In addition, I compute standard errors for each of these estimated parameters for each firm. Table V displays summary statistics for the cross-sectional distribution of the standard errors for each of the firm-specific parameter estimates. The first row of the table displays the mean standard error for the firm-specific parameter estimates. For example, the mean standard error on the estimated  $\alpha_i$  across the 2,505 firms is 0.073.

In Figure 6 I plot the distribution of the estimated  $\alpha_i$ 's along with this distribution shifted up and down by one standard error. The blue line in the figure is the distribution of the estimated  $\alpha_i$  reproduced from Panel A of Figure 5. For each firm i, I add the computed standard error  $SE(\alpha_i)$  to its estimated  $\alpha_i$ . The green line plots the distribution these values  $\alpha_i + SE(\alpha_i)$ . The red line represents an analogous distribution where each firm's standard error is subtracted from its estimated  $\alpha_i$ .

## 6 Characterizing the Estimated Default Costs

In this section I characterize the estimated firm-level default costs by examining how they relate to firm characteristics, credit ratings, and industry. Using data that was not included in the estimation procedure allows me to check whether the estimates are consistent with previously identified determinants of leverage and default costs. This not only gives an external validation check of the estimates obtained from the structural model, but also provides insights into the determinants of a firm's default costs.

In Table VI, I display summary statistics for the estimated default costs by industry. The industries are grouped according to the Fama-French 17 industry classification, with utilities and financials excluded from the sample.<sup>22</sup> Note that while there is some variation in the mean default cost across industry, there is substantial intraindustry variation. In Table VII, I present the mean value for all four firm-specific parameters by industry.

Table VIII displays the average estimated default costs and cash flow parameters by credit rating. The table shows that the average estimated default costs are increasing in the quality of credit rating. Since firms with high default costs choose leverage such that their probability of default is low, these firms are likely to be those that have a high credit rating, at least at their optimal financing date. This implies that firms which at one point had a high credit rating and later defaulted, the so-called fallen angels, should have higher than average default costs. This prediction is consistent with the findings of Davydenko, Strebulaev, and Zhao (2012), who find empirically that fallen angels have realized default costs significantly higher than those of original-issue junk issuers.<sup>23</sup>

In Table IX, I present regressions of the estimated default costs on various firm characteristics. I present six different specifications in which I compare the results with and without controls for leverage and industry fixed effects. While not all statistically significant, the

<sup>&</sup>lt;sup>22</sup>The Fama-French industry classification is according to Standard Industrial Classification (SIC) codes, which are available for the firms in the Compustat database. Details of the classification are provided on Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html.

<sup>&</sup>lt;sup>23</sup>The original-issue junk issuers are those firms rated speculative grade at the time when the bonds are issued.

relationship between default costs and firm characteristics generally appear consistent with intuition and previously identified determinants.

As shown in Table IX, firms with higher market-to-book ratios and investment rates appear to have higher default costs, even after controlling for leverage. These characteristics are often associated with growth firms. Distress or default is likely to be costly for these firms, both because they have less value in physical assets and because such an event would likely result in the firm losing its growth options. Additionally, while not statistically significant, the R&D/Sales ratio is positively correlated with default costs. Similar to firms with growth options, distress or default is likely to be costly for R&D-intensive firms as this intangible capital may be more difficult for the firm to liquidate or transfer. Finally, firms with higher cash to asset ratios appear to be those with higher default costs, which consistent with a hedging motive.

### 7 Estimation of the Selection Bias in Default Costs

In the simulation of Section 4, I assumed  $\alpha_i \sim U[0,1]$  and fixed the three firm-specific cash flow parameters,  $\mu_i, \beta_i, \sigma_i^F$ , to be identical across firms. In that case, the selection bias computed in  $\alpha$ , while quantitatively significant, is not independent of the parameter distribution chosen. Thus, the bias calculation of Section 4, while illustrative, does not provide an actual estimate of the magnitude of the bias.

To estimate the selection bias in default costs, I use the firm-specific parameters estimated in the SMM of Section 5 to simulate the model again, but under the estimated joint cross-sectional distribution of the firm-specific parameters. Aggregating the firm-specific estimates obtained from the SMM, I have an estimated four-dimensional joint distribution over the cross-section. I then simulate the model under this joint distribution and estimate the selection bias in the cost of default. As in the simulation of Section 4, I simulate a panel of 5,000 firms at a quarterly frequency for a 35 year period and repeat the simulation 5,000 times. In each simulation, I collect the firms that defaulted in the sample period and compute an average  $\alpha$  for this conditional sample of simulated defaults. Thus, I obtain 5,000 mean

values for  $\alpha$ .

Figure 7 displays the distribution of these conditional mean  $\alpha$ 's across simulations. The red vertical line indicates the true unconditional mean  $\alpha$  of the estimated distribution obtained from the SMM. Note that this is also the distribution under which the model is simulated. As indicated by the figure, in none of the 5,000 sample simulations is the conditional average  $\alpha$  computed from the sample of defaulted firms as large as the true unconditional mean.

In Table X, I present the estimated selection bias in the average cost of default. Averaging across the 5,000 simulations, the mean cost of default for the defaulted firms is 0.246, or 24.6% of firm value. In contrast, the average default cost among all firms is 44.5%. Thus, the estimated selection bias in default costs is quantitatively large. Using the sample of ex post defaults leads one to conclude that the average default costs are 24.6% of firm value when, in fact, the true mean of the distribution of these costs is 44.5%. In other words, the average firm expects to incur costs in default that are nearly twice as large as what is inferred by estimating these costs from the sample of defaulted firms. Furthermore, the average default cost among defaulted firms of 24.6% generated by the estimated model is closely in line with existing empirical estimates from the sample of defaulted firms. For example, Andrade and Kaplan (1998) estimate default costs of 10-23% of firm value from a sample of highly leveraged transactions. More recently, Davydenko, Strebulaev, and Zhao (2012) estimate an average default cost of 21.7% from a sample of 175 defaulted firms.

Figure 8 illustrates that the bias affects the entire distribution of default costs, not just the mean value. The figure compares the estimated distribution of expected default costs (Panel A) with the distribution of observed default costs from the sample of defaulted firms generated by simulating the estimated model (Panel B). As shown in the figure, the selection bias has the effect of shifting the entire distribution. While defaults of high default cost firms are observed, these are rare and infrequent. As a result, the observed sample of default costs is a biased sample that understates the magnitude of default costs.

## 8 Conclusion

This paper argues that ex ante heterogeneity in firms' expected default costs has important implications for the levels of leverage, credit spreads, and default rates observed in the data. Because firms internalize their expected default costs, those firms with higher costs optimally choose lower levels of leverage, all else equal. As a result, these firms are less likely to default than those firms with lower costs. The estimates of default costs from a sample of defaulted firms, is therefore biased, understating the expected costs faced by the average firm. Since it is the latter that determines a firm's optimal leverage, firms may appear underlevered when, in fact, they simply have high expected default costs.

Using a dynamic capital structure model, I estimate a quantitatively significant selection bias in default costs. My results suggest that many firms may face higher expected default costs than what is indicated by the empirical sample of defaulted firms. Furthermore, the selection bias in default costs that I estimate can help to explain the low leverage ratios adopted by many firms in the data in the context of a tradeoff model of capital structure.

Table I: **Parameters** 

This table reports the parameter values used in simulating the model described in Section 4. Where applicable, values are quarterly. All parameters are identical across firms except for  $\alpha$ , which is distributed cross-sectionally according to U[0,1]. The aggregate earnings parameters and probability of a regime change are estimated via maximum likelihood using aggregate earnings data. See the appendix for details on the estimation procedure.

Parameter	Symbol	State 1	State 2
Default Costs	$\alpha$	_	_
Aggregate Earnings Growth Rate	$\mu_A$	0.0192	-0.0076
Aggregate Earnings Volatility	$\sigma_A$	0.0366	0.0770
Idiosyncratic Earnings Volatility	$\sigma_f$	0.130	0.130
Market Sharpe Ratio	arphi	0.140	0.238
Instantaneous Risk-free Rate	$r_f$	0.006	0.009
Probability of Regime Change	$\lambda$	0.07	0.10
Tax Rate on Corporate Earnings	$ au_{\pi}$	0.35	0.35
Tax Rate on Dividends	$ au_d$	0.12	0.12
Tax Rate on Interest Income	$ au_i$	0.296	0.296
Proportional Debt Issuance Cost	$\phi_D$	0.015	0.015

Table II: Simulation Results

This table displays various moments from the simulated model and their empirical counterparts. Model moments are produced by simulating a panel of 5,000 firms at quarterly frequency for 35 years. The simulation is repeated 5,000 times. The simulation is performed at a quarterly frequency and all values are annualized. The leverage statistics are computed by taking the cross-sectional mean or standard deviation at each quarter of the simulation. A time series average of this statistic is computed for each simulation. The value reported is the mean across the 5,000 simulations. The model parameters used for the simulation can be found in Table I. Aggregate earnings data is from NIPA, leverage moments and the cross-sectional dispersion of earnings are computed from Compustat data. Recovery rate and cumulative default probability data are from Moody's. Book leverage is (book debt)/(book debt + book equity), quasi-market leverage is (book debt)/(book debt + market equity).

Moment	Model	Data			
Excess Equity Ret	0.049	0.063			
Aggregate Earnings Growth	0.039	0.034			
Earnings Cross-Sectional Std	0.130	0.152			
Book Leverage Mean	0.207	0.228			
Book Leverage Cross-Sectional Std	0.153	0.184			
Quasi-Market Leverage Mean	0.297	0.280			
Quasi-Market Leverage Cross-Sectional Std	0.218	0.260			
Recovery Rate Mean	0.423	0.375			
Recovery Rate Cross-Sectional Std	0.137	0.257			
Cumulative Default Probability					
1 year	0.014	0.016			
5 year	0.069	0.071			
10 year	0.132	0.111			
15 year	0.188	0.142			

# Table III: Simulated Default Probabilities and Credit Spreads by Credit Rating

This table displays 10-year default probabilities and credit spreads by credit rating from the simulated model of Section 4. At each date in the simulation, each firm's current 10-year default probability and credit spread on a 10-year bond are computed via Monte Carlo. The firms are then assigned a credit rating at each date according to their current default probability.

Panel A: 10 Year Credit Spread Over Aaa (bps)

Rating	Model	Data
A	15	36
Baa	73	81
Ba	222	253
В	415	386

Panel B: 10 Year Cumulative Default Probability by Credit Rating (%)

Rating	Model	Data
Aaa	0.69	0.50
A	2.63	2.05
Baa	8.93	4.85
Ba	22.04	19.96
В	36.37	44.38

## Table IV: Cross-sectional Statistics for Firm-Specific Parameter Estimates

This table reports summary statistics for the firm-specific parameter estimates obtained from the SMM of Section 5. The firm-specific parameters consist of three cash flow parameters ( $\mu_i$ ,  $\beta_i$ , and  $\sigma_i^F$ ) and the cost of default parameter  $\alpha_i$ . Firm *i*'s earnings in the model evolve according to

$$\frac{dX_{i,t}}{X_{i,t}} = (\mu_i + \beta_i \mu_A(\nu_t))dt + \beta_i \sigma_A(\nu_t)dW_t^A + \sigma_{i,F}dW_t^{i,F}$$

where  $\mu_i$  represents a firm fixed effect for the expected earnings growth rate,  $\beta_i$  is the loading of the firm's cash flows on the aggregate earnings shock, and  $\sigma_i^F$  is the volatility of the firm's idiosyncratic earnings shocks. The fraction of unlevered firm value lost in default for firm i is given by  $\alpha_i$ , where the unlevered value is defined in equation (5). Panel A displays cross-sectional moments for the firm-specific parameter estimates. Note that the  $\mu$  row reports statistics for firms' unconditional expected growth rate, not the firm specific component  $\mu_i$ . The cross-sectional correlation of the parameter estimates are shown in Panel B. Panel C displays Spearman rank correlations for the estimated parameters with firm data moments. The sample consists of 2,505 firms from the merged Compustat and CRSP databases. See the Appendix for further details.

Panel A: Parameter Estimate Summary Statistics

	Mean	$\mathbf{Median}$	$\mathbf{Std}$
$\alpha_i$	0.445	0.368	0.270
$\sigma_i^F$	0.132	0.147	0.055
$eta_i$	1.278	1.000	0.577
$\mu$	0.004	0.001	0.007

Panel B: Correlation of Parameter Estimates

	$lpha_i$	$\sigma_i^{\scriptscriptstyle F}$	$eta_i$	$\mu_i$
$-\alpha_i$	1			
$\sigma_i^F$	-0.270	1		
$eta_i$	0.320	0.023	1	
$\mu_i$	0.358	-0.125	0.567	1

Panel C: Spearman Rank Correlations

$lpha_i$	$\sigma_i^{\scriptscriptstyle \Gamma}$	$eta_i$	$\mu_i$
-0.862	0.095	-0.357	-0.326
0.046	-0.085	0.274	0.315
-0.144	0.660	0.191	0.159
0.288	-0.131	0.286	0.562
-0.743	0.292	-0.484	-0.504
0.135	-0.059	0.207	0.154
	-0.862 0.046 -0.144 0.288 -0.743	-0.862 0.095 0.046 -0.085 -0.144 0.660 0.288 -0.131 -0.743 0.292	-0.862     0.095     -0.357       0.046     -0.085     0.274       -0.144     0.660     0.191       0.288     -0.131     0.286       -0.743     0.292     -0.484

Table V:
Distribution Statistics for Firm-level Standard Errors

This table presents distribution statistics for the cross-section of standard errors on the firm-specific parameter estimates obtained in the SMM procedure of Section 5. For each firm, four firm-level parameters are estimated with standard errors. The table displays statistics for the cross-sectional distribution of these standard errors. For more details on the estimation, see Section 5.

	$\mathbf{SE}(\alpha)$	$\mathbf{SE}(\sigma^F)$	$\mathbf{SE}(eta)$	$\mathbf{SE}(\mu)$
Mean	0.073	0.009	0.478	0.005
$\mathbf{Std}$	0.176	0.006	0.393	0.007
$\mathbf{Q}1$	0.027	0.004	0.179	0.002
Median	0.043	0.008	0.378	0.003
$\mathbf{Q3}$	0.072	0.013	0.655	0.006

Table VI:

Default Cost Estimates by Industry

This table reports summary statistics by industry for the estimated  $\alpha$ 's obtained in the firm-level SMM. Industries correspond to one of the 17 Fama-French industry index, based on SIC codes. Financials and utilities are excluded. Q1 and Q3 report the 25th and 75th percentiles, respectively. The final column, labeled N, provides the number of firms in each industry classification.

	Mean	$\mathbf{Std}$	$\mathbf{Q}1$	Median	$\mathbf{Q3}$	${f N}$
Food	0.389	0.255	0.211	0.316	0.474	128
Mining and Minerals	0.463	0.275	0.263	0.421	0.632	36
Oil	0.364	0.262	0.211	0.316	0.421	158
Clothing	0.452	0.273	0.263	0.368	0.632	110
Cons Durable	0.422	0.267	0.263	0.368	0.579	113
Chemicals	0.435	0.248	0.316	0.368	0.474	62
Drugs, Perfume, Tobacco	0.532	0.259	0.368	0.474	0.684	88
Construction	0.374	0.206	0.211	0.368	0.474	143
Steel	0.369	0.191	0.263	0.342	0.421	64
Fabricated Products	0.350	0.203	0.211	0.316	0.421	46
Machinery	0.489	0.250	0.316	0.421	0.632	411
Automobiles	0.397	0.205	0.263	0.368	0.474	58
Transportation	0.413	0.181	0.303	0.368	0.487	41
Retail Stores	0.442	0.266	0.263	0.368	0.526	251
Other	0.474	0.302	0.263	0.421	0.684	752

Table VII:
Parameter Estimates by Industry

This table reports the mean firm-specific parameter estimates by industry. Estimates are obtained from the SMM procedure described in Section 5. Industries correspond to one of the 17 Fama-French industry index, based on SIC codes. Financials and utilities are excluded.

	$\alpha$	$\sigma^F$	$\beta$	$\mu$
Food	0.389	0.135	1.195	0.003
Mining and Minerals	0.463	0.141	1.319	0.005
Oil	0.364	0.134	1.246	0.005
Clothing	0.452	0.137	1.251	0.001
Cons Durable	0.422	0.140	1.209	0.001
Chemicals	0.435	0.121	1.131	0.002
Drugs, Perfume, Tobacco	0.532	0.112	1.430	0.004
Construction	0.374	0.146	1.146	0.001
Steel	0.369	0.147	1.128	0.001
Fabricated Products	0.350	0.150	1.141	0.001
Machinery	0.489	0.133	1.338	0.005
Automobiles	0.397	0.140	1.162	0.002
Transportation	0.413	0.136	1.085	0.001
Retail Stores	0.442	0.131	1.235	0.003
Other	0.474	0.125	1.363	0.005

Table VIII:
Parameter Estimates by Credit Rating

This table reports the mean firm-specific parameter estimates by credit rating for those firms in the sample for which a credit rating is available. The parameter estimates are obtained in the SMM of Section 5.

	$\alpha$	$\sigma^F$	$\beta$	$\mu$
Aaa	0.568	0.094	0.840	0.002
$\mathbf{Aa}$	0.585	0.093	1.128	0.003
${f A}$	0.445	0.102	1.031	0.002
Baa	0.419	0.112	1.100	0.003
$\mathbf{Ba}$	0.313	0.125	1.234	0.004
В	0.305	0.137	1.296	0.004
Caa-C	0.189	0.167	1.400	0.008

Table IX:
Regressions of Estimated Default Costs on Firm Characteristics

This table reports regressions of the estimated firm-specific default costs,  $\alpha$ , on firm characteristics. The firm-specific default costs,  $\alpha$ , are estimated using the SMM procedure described in Section 5. Unless indicated otherwise, independent variables are a time series mean of the data available for each firm. In the regressions, all independent variables are normalized by their (cross-sectional) standard deviation, thus the coefficient can be interpreted as the absolute change in  $\alpha$  for a one standard deviation change in the independent variable. Regressions (4), (5), and (6) include industry fixed effects for the 15 Fama-French industries included in the sample. Robust standard errors are in parentheses. For more details on the data construction see the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$\widehat{lpha}$	$\widehat{lpha}$	$\widehat{lpha}$	$\widehat{lpha}$	$\widehat{lpha}$	$\widehat{lpha}$
Book Leverage		-0.200***	-0.216***		-0.202***	-0.221***
		(0.004)	(0.008)		(0.004)	(0.008)
Cash/Assets			0.008			0.012
			(0.007)			(0.007)
R&D/Sales			0.015			0.018*
			(0.009)			(0.010)
PPE/Assets	-0.039***	0.005	0.019***	-0.041***	0.008*	0.016**
	(0.006)	(0.004)	(0.007)	(0.007)	(0.004)	(0.008)
I/K	0.050***	0.014***	0.026***	0.052***	0.013***	0.021**
	(0.007)	(0.004)	(0.008)	(0.007)	(0.004)	(0.009)
Earnings/Assets	0.074***	0.030***	0.033***	0.074***	0.030***	0.033***
	(0.006)	(0.004)	(0.007)	(0.006)	(0.004)	(0.008)
M/B	0.016**	0.024***	0.034***	0.014**	0.024***	0.031***
	(0.007)	(0.005)	(0.007)	(0.007)	(0.005)	(0.008)
COGS/Sales	-0.024***	-0.007*	-0.008	-0.017***	-0.006	-0.003
	(0.006)	(0.004)	(0.008)	(0.007)	(0.004)	(0.008)
log(Assets)	-0.010**	-0.003	0.000	-0.010**	-0.002	0.004
	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.006)
Constant	0.444***	0.443***	0.437***	0.445***	0.442***	0.433***
	(0.005)	(0.003)	(0.007)	(0.005)	(0.003)	(0.007)
	, ,	, ,				
Observations	2,381	2,381	670	2,340	2,340	653
R-squared	0.206	0.663	0.733	0.185	0.651	0.723
Industry FE	N	N	N	Y	Y	Y

Robust standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Regression of Estimated  $\alpha$ 's on Firm Characteristics

# Table X: Estimated Bias in Default Costs

This table presents the inferred mean default costs from the sample of defaulted firms in the simulated data, using the parameter distributions estimated in the SMM of Section 5. That is, I take the 4-dimensional joint cross-sectional distribution for the firm-specific parameters and simulate a panel of firms with this parameter distribution. The panel consists of 5,000 firms simulated at a quarterly frequency for 35 years for each simulation. 5,000 simulations are performed. For each simulation, the  $\alpha$ 's for the firms which defaulted are collected and a mean value is computed for each simulation. The Mean of the "Ex Post Mean  $\widehat{\alpha}$ " is the mean across simulations of these computed means. The true mean  $\alpha$  indicates the unconditional mean value of  $\alpha$  from the cross-sectional distribution estimated in the SMM of Section 5.

Ex Post Mean $\hat{\alpha}$	"True" Mean Estimated $\alpha$	Bias
0.246	0.445	-0.199

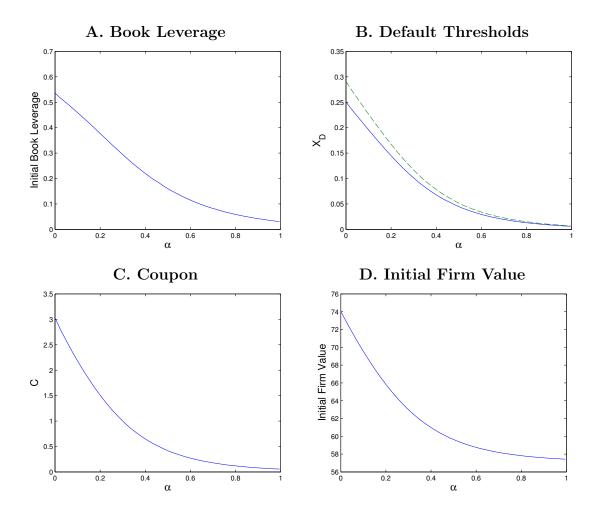


Figure 1: Optimal Policies as a Function of Default Costs,  $\alpha$ . Panel A plots the optimally chosen initial book leverage for varying  $\alpha$ . Panel B displays the equityholders' optimal default threshold for the high (solid line) and low (dashed line) states. Panel C shows the optimal coupon on the firm's perpetuity. Panel D shows the initial total firm value (sum of initial debt and initial levered equity), for optimally chosen leverage as a function of the default costs. In all cases, the initial state at time 0 is the high state. The time-0 cash flow,  $X_0$ , is normalized to 1. The other parameters are given in Table I.

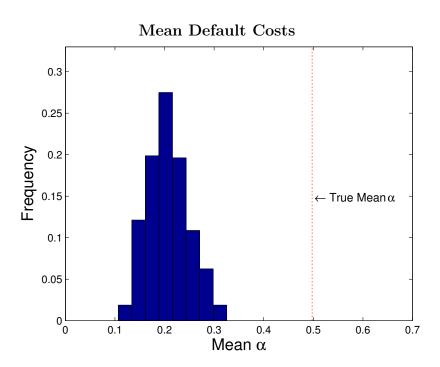


Figure 2: Distribution of Mean Default Costs from the Sample of Defaulted Firms. A panel of 5,000 firms is simulated over 35 years and the simulation is repeated 5,000 times. For each simulation, a conditional distribution for  $\alpha$  is constructed from the sample of firms that defaulted in the simulation. The vertical dotted line represents the mean of the true, unconditional distribution of  $\alpha$  assumed in the simulation. The parameters used can be found in Table I.

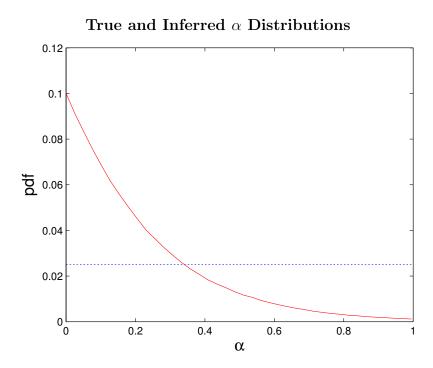


Figure 3: Distribution of True and "Inferred"  $\alpha$ . A panel of 5,000 firms is simulated over 35 years and the simulation is repeated 5,000 times. The sample of defaulted firms is aggregated over all simulations and the default costs for this sample are plotted with the solid red line. The horizontal blue line indicates the true assumed distribution of default costs for the entire population of firms, which is  $U \sim [0,1]$ .

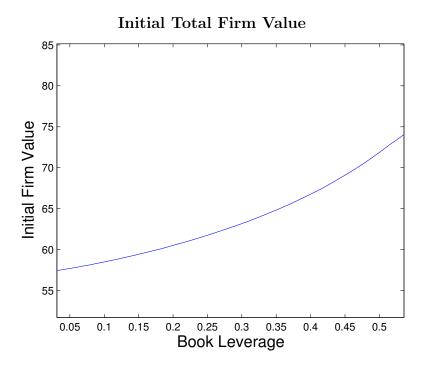


Figure 4: Initial Firm Value as a Function of Optimal Leverage. This figure shows the initial total firm value as a function of the optimal leverage chosen at time 0. The initial state is the high state. The optimal book leverage values displayed are for  $\alpha \in [0, 1]$ .

#### A. Distribution of Estimated $\alpha_i$ B. Distribution of Estimated $\beta_i$ Estimated Distribution for $\alpha$ Estimated Distribution for $\beta_i$ Estimated Density O 0 0 80 **Estimated Density** 0.4 0.5 0.2 1.5 β<sub>i</sub> 2.5 0.2 0.4 0.8 0.5 0.6 2 D. Distribution of Estimated $\sigma_i^F$ C. Distribution of Estimated $\mu_i$ Estimated Distribution for $\mu_i$ Estimated Distribution for σ<sub>i</sub><sup>F</sup> 100 90 80 Estimated Density ω 4 σ **Estimated Density** 60 50 40 30 20 10 -0.02 -0.01 0 0.01 0.02 0.03 0.05 0.1 0.15 0.2 0.25

Figure 5: Estimated Cross-Sectional Distributions for the Firm-Specific Parameters. This figure displays the cross-sectional distribution of the firm-specific parameter estimates from the SMM described in Section 5.

#### **Estimated Default Costs with Standard Errors**

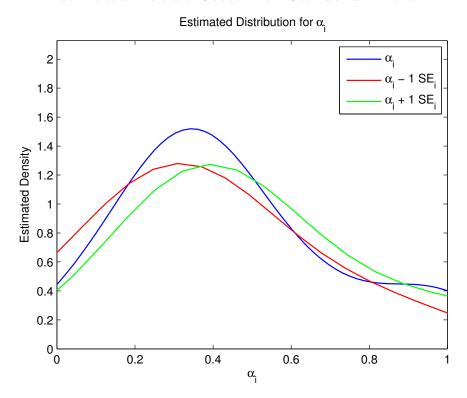


Figure 6: This figure plots the cross-sectional distribution for the estimated  $\alpha_i$ 's (blue line) along with the distribution of all estimates plus/minus a standard error. That is, the red line indicates the cross-sectional distribution of  $\alpha_i - SE(\alpha_i)$ , where  $SE(\alpha_i)$  is the standard error computed for firm i's estimated  $\alpha_i$ . Similarly, the green line plots  $\alpha_i + SE(\alpha_i)$ .

#### Simulated Mean Default Costs from Estimated Parameter Distributions

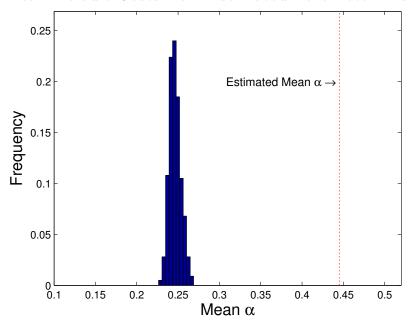
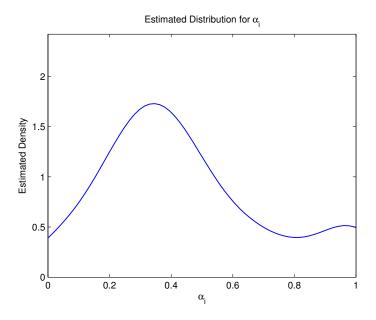


Figure 7: Distribution of Median and Mean Default Costs from the Sample of Defaulted Firms. A panel of 5,000 firms is simulated over 35 years and the simulation is repeated 5,000 times. For each simulation, a mean value of  $\alpha$  is computed from the population of firms which defaulted during the simulation. The histogram indicates the distribution mean  $\alpha$ 's across the 5,000 simulations. The vertical red dashed lines indicates the estimated unconditional mean  $\alpha$  from the SMM procedure of Section 5

#### A. Distribution of Estimated $\alpha$



#### B. Distribution of $\alpha$ for Simulated Defaults

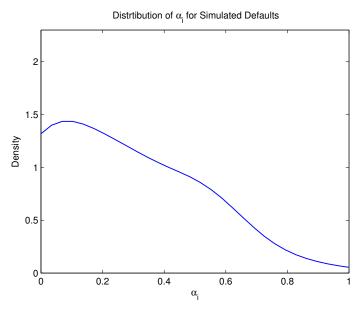


Figure 8: Estimated Distribution of Default Costs vs. Distribution for Simulated Defaults. This figure compares the estimated unconditional distribution of default costs,  $\alpha$ , with the conditional distribution from the sample of simulated defaults. The estimated distribution, which is displayed in Panel A, is obtained from the firm-specific SMM described in Section 5. I simulate 5,000 model economies under the estimated joint cross-sectional distribution of  $\{\alpha_i, \mu_i, \beta_i, \sigma_i^F\}$  and collect the sample of firms which defaulted in each simulation. Panel B plots the distribution of default costs, aggregated over all simulations, of the firms that defaulted.

# References

- Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan. 2007. "Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries." *Journal of Financial Economics* 85 (3):787–821.
- Almeida, Heitor and Thomas Philippon. 2007. "The risk-adjusted cost of financial distress." The Journal of Finance 62 (6):2557–2586.
- Altinkilic, Oya and Robert S. Hansen. 2000. "Are there economies of scale in underwriting fees? Evidence of rising external financing costs." Review of Financial Studies 13 (1):191.
- Altman, Edward I. 1984. "A further empirical investigation of the bankruptcy cost question." Journal of Finance 39 (4):1067–1089.
- Altman, Edward I., Brooks Brady, Andrea Resti, and Andrea Sironi. 2005. "The Link between Default and Recovery Rates: Theory, Empirical Evidence, and Implications." The Journal of Business 78 (6):2203–2228.
- Andrade, Gregor and Steven N. Kaplan. 1998. "How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed." *The Journal of Finance* 53 (5):1443–1493.
- Asquith, Paul, Robert Gertner, and David Scharfstein. 1994. "Anatomy of financial distress: An examination of junk-bond issuers." The Quarterly Journal of Economics 109 (3):625–658.
- Bhamra, Harjoat S., Lars-Alexander. Kuehn, and Ilya A. Strebulaev. 2010a. "The aggregate dynamics of capital structure and macroeconomic risk." *Review of Financial Studies* 23 (12):4187–4241.
- Bhamra, Harjoat S., Lars-Alexander Kuehn, and Ilya A. Strebulaev. 2010b. "The levered equity risk premium and credit spreads: A unified framework." *Review of Financial Studies* 23 (2):645–703.

- van Binsbergen, Jules H., John R. Graham, and Jie Yang. 2010. "The Cost of Debt." *Journal of Finance* 65 (6):2089–2136.
- Bris, Arturo, Ivo Welch, and Ning Zhu. 2006. "The costs of bankruptcy: Chapter 7 liquidation versus Chapter 11 reorganization." *Journal of Finance* 61 (3):1253–1303.
- Chen, Hui. 2010. "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure." *Journal of Finance* 65 (6):2171–2212.
- Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein. 2009. "On the relation between the credit spread puzzle and the equity premium puzzle." *Review of Financial Studies* 22 (9):3367–3409.
- Davydenko, Sergei A., Ilya A. Strebulaev, and Xiaofei Zhao. 2012. "A Market-Based Study of the Costs of Default." Working Paper .
- Duffie, Darrell. 2001. Dynamic Asset Pricing Theory. Princeton University Press.
- Duffie, Darrell and Kenneth J. Singleton. 1993. "Simulated Moments Estimation of Markov Models of Asset Prices." *Econometrica* 61 (4):929–952.
- Elkamhi, Redouane, Jan Ericsson, and Christopher A. Parsons. 2010. "The cost of financial distress and the timing of default." Working paper.
- Fischer, Edwin O., Robert Heinkel, and Josef Zechner. 1989. "Dynamic capital structure choice: Theory and tests." *Journal of Finance* 44 (1):19–40.
- Franks, Julian R. and Walter N. Torous. 1989. "An empirical investigation of US firms in reorganization." *Journal of Finance* 44 (3):747–769.
- George, Thomas J. and Chuan-Yang Hwang. 2010. "A resolution of the distress risk and leverage puzzles in the cross section of stock returns." *Journal of Financial Economics* 96 (1):56–79.

- Gilson, Stuart C. 1997. "Transactions costs and capital structure choice: Evidence from financially distressed firms." *Journal of Finance* 52 (1):161–196.
- Goldstein, Robert S., Nengjiu Ju, and Hayne Leland. 2001. "An EBIT-based model of optimal capital structure." *Journal of Business* 74 (4):483–512.
- Graham, John R. 2000. "How big are the tax benefits of debt?" Journal of Finance 55 (5):1901–1941.
- Guo, X. and Q. Zhang. 2004. "Closed-form solutions for perpetual American put options with regime switching." SIAM Journal on Applied Mathematics 64 (6):2034–2049.
- Hackbarth, Dirk, Jianjun Miao, and Erwan Morellec. 2006. "Capital structure, credit risk, and macroeconomic conditions." *Journal of Financial Economics* 82 (3):519–550.
- Hamilton, James D. 1989. "A new approach to the economic analysis of nonstationary time series and the business cycle." *Econometrica: Journal of the Econometric Society* 57 (2):357–384.
- ——. 1994. Time Series Analysis. Princeton University Press.
- Harrison, J. Michael and David M. Kreps. 1979. "Martingales and arbitrage in multiperiod securities markets." *Journal of Economic Theory* 20 (3):381–408.
- Hennessy, Christopher A. and Toni M. Whited. 2007. "How costly is external financing? Evidence from a structural estimation." *Journal of Finance* 62 (4):1705.
- Jarrow, Robert A., David Lando, and Stuart M. Turnbull. 1997. "A Markov model for the term structure of credit risk spreads." *Review of Financial Studies* 10 (2):481.
- Jobert, A. and LCG Rogers. 2006. "Option pricing with Markov-modulated dynamics." SIAM Journal on Control and Optimization 44 (6):2063–2078.
- Korteweg, Arthur. 2010. "The Net Benefits to Leverage." Journal of Finance 65 (6):2137–2170.

- Leland, Hayne E. 1994. "Corporate Debt Value, Bond Covenants, and Optimal Capital Structure." *Journal of Finance* 49:1213–1213.
- Merton, Robert C. 1974. "On the pricing of corporate debt: The risk structure of interest rates." *Journal of Finance* 29 (2):449–470.
- Miller, Merton H. 1977. "Debt and taxes." Journal of Finance 32 (2):261–275.
- Morellec, Erwan, Boris Nikolov, and Norman Schuerhoff. 2010. "Dynamic capital structure under managerial entrenchment: Evidence from a structural estimation." Working Paper, University of Lausanne.
- Newey, Whitney K. and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3):703–708.
- Nikolov, Boris and Toni M. Whited. 2010. "Agency conflicts and cash: Estimates from a structural model." .
- Ofek, Eli. 1993. "Capital structure and firm response to poor performance:: An empirical analysis." *Journal of Financial Economics* 34 (1):3–30.
- Opler, Tim C. and Sheridan Titman. 1994. "Financial distress and corporate performance." Journal of Finance 49 (3):1015–1040.
- Pulvino, Todd C. 1998. "Do Asset Fire Sales Exist? An Empirical Investigation of Commercial Aircraft Transactions." *The Journal of Finance* 53 (3):939–978.
- Taillard, Jerome. 2010. "Thriving in the midst of financial distress? An analysis of firms exposed to asbestos litigation." Working paper.
- Warner, Jerold B. 1977. "Bankruptcy, absolute priority, and the pricing of risky debt claims." Journal of Financial Economics 4 (3):239–276.

Weiss, Lawrence A. 1990. "Bankruptcy resolution:: Direct costs and violation of priority of claims." *Journal of Financial Economics* 27 (2):285–314.

# Appendices

## A Pricing Kernel, Risk-Neutral Measure

Given the exogenously specified process for the pricing kernel, the risk-neutral measure can be derived.<sup>24</sup> The pricing kernel,  $\pi_t$ , evolves according to

$$\frac{d\pi_t}{\pi_t} = -r(\nu_t)dt - \varphi^m(\nu_t)dW_t^m$$

Define the density process for the risk-neutral measure by

$$\xi_t = E_t \left[ \frac{dQ}{dP} \right]$$

We know this density process and the pricing kernel are related by<sup>25</sup>

$$\xi_t = B_t \pi_t$$

where

$$B_t = exp\left\{ \int_0^t r(\nu_s)ds \right\}$$

is the time t price of a bond paying the riskless rate and  $B_0$  has been normalized to 1. Applying Itô's Lemma gives

$$d\xi_t = B_t d\pi_t + \pi_t dB_t$$

Plugging in the expression for  $d\pi_t$ ,

$$d\xi_t = B_t[-r(\nu_t)\pi_t dt - \varphi^m(\nu_t)\pi_t dW_t^m] + \pi_t dB_t$$

Replacing  $\pi_t$  with  $\frac{\xi_t}{B_t}$  and dividing through by  $\xi_t$  gives

$$\frac{d\xi_t}{\xi_t} = -r(\nu_t)dt - \varphi^m(\nu_t)dW_t^m + \frac{1}{B_t}dB_t$$

 $<sup>^{24}</sup>$ Since the horizon is infinite, the risk-neutral measure,  $\mathcal{Q}$ , that will be used for pricing contingent claims is not an equivalent probability measure to the physical measure,  $\mathcal{P}$ . Still, the risk-neutral measure  $\mathcal{Q}$  will have the necessary properties for risk-neutral pricing. See Duffie (2001), Section 6N, for more details.

<sup>&</sup>lt;sup>25</sup>See Harrison and Kreps (1979).

Itô's Lemma implies

$$dB_t = r(\nu_t)dt$$

Thus the density process,  $\xi_t$ , evolves according to

$$\frac{d\xi_t}{\xi_t} = -\varphi^m(\nu_t)dW_t^m$$

Applying Girsanov's Theorem, we have a new Brownian motion under the risk-neutral measure, given by

$$d\widehat{W}_t^m = dW_t^m + \varphi^m(\nu_t)dt$$

Note that the firm-specific Brownian motion,  $W_t^{f,n}$ , that generates the idiosyncratic shocks to firm n's cash flows is independent of the Brownian motion,  $W_t^m$  generating systematic shocks to the economy. Thus  $W_t^{f,n}$  is still a Brownian motion under the risk-neutral measure for all firms n. Thus, under the risk-neutral measure, cash flows for firm n evolve according to

$$\frac{dX_t^n}{X_t^n} = \widehat{\mu}^n(\nu_t)dt + \sigma_m^n(\nu_t)d\widehat{W}_t^m + \sigma_f^n dW_t^{f,n}$$

where  $\widehat{\mu}^n(\nu_t)$  is the drift under the risk-neutral measure,

$$\widehat{\mu}^n(\nu_t) = \mu^n(\nu_t) - \sigma_m^n(\nu_t)\varphi^m(\nu_t).$$

The total volatility of the cash flows of firm n is given by

$$\sigma_X^n(\nu_t) = \sqrt{(\sigma_m^n(\nu_t))^2 + (\sigma_f^n)^2}$$

Additionally, the two Brownian motions driving the idiosyncratic and systematic shocks to firm n's cash flows under the risk-neutral measure can be aggregated into a single Brownian motion (under the risk-neutral measure) for firm n which is given by

$$d\widehat{W}_t^n = \frac{\sigma_m^n(\nu_t)}{\sigma_X^n(\nu_t)} d\widehat{W}_t^m + \frac{\sigma_f^n}{\sigma_X^n(\nu_t)} dW_t^{f,n}.$$

So the evolution of firm n's cash flows under the risk-neutral measure can be expressed as

$$\frac{dX_t^n}{X_t^n} = \widehat{\mu}^n(\nu_t)dt + \sigma_X^n(\nu_t)d\widehat{W}_t^n$$

### B Solving for Unlevered Firm Value

Here I show how to solve for the unlevered firm value.<sup>26</sup> The pair of ODEs characterizing the unlevered firm value has an associated characteristic function given by:

$$g_1(\beta)g_2(\beta) = \lambda_1 \lambda_2 \tag{23}$$

where

$$g_1(\beta) = \lambda_1 + r - (\mu_1 - \frac{1}{2}\sigma_1^2)\beta - \frac{1}{2}\sigma_1^2\beta^2$$
 (24)

$$g_2(\beta) = \lambda_2 + r - (\mu_2 - \frac{1}{2}\sigma_2^2)\beta - \frac{1}{2}\sigma_2^2\beta^2$$
 (25)

This characteristic function has four distinct roots  $\beta_1 < \beta_2 < 0 < \beta_3 < \beta_4$ . The general form of the solution is given by

$$A^{1}(X) = \phi_{1}(X) + \sum_{i=1}^{4} G_{i} x^{\beta_{i}}$$
(26)

$$A^{2}(X) = \phi_{2}(X) + \sum_{i=1}^{4} H_{i} x^{\beta_{i}}$$
(27)

$$H_i = l(\beta_i)G_i = \frac{g_1(\beta_i)}{\lambda_1}G_i = \frac{\lambda_2}{g_2(\beta_i)}G_i$$
(28)

However boundedness conditions on the unlevered firm value need to be imposed. These are

$$\lim_{x \to \infty} \frac{A^i(x)}{x} < \infty \quad \text{and} \quad \lim_{x \to 0} A^i(x) < \infty$$
 (29)

<sup>&</sup>lt;sup>26</sup>The exposition follows Guo and Zhang (2004). See also Chen (2010) and Jobert and Rogers (2006).

These two conditions imply  $\beta_i = 0$ , i = 1, ..., 4. Thus the unlevered firm value has the form:

$$A^{i}(X) = \phi_{i}(X) \tag{30}$$

We conjecture that the unlevered firm value is affine in X. That is,

$$A^{i}(X) = c_{i}X + d_{i} \tag{31}$$

Furthermore,  $d_i = 0$ , i = 1, 2, since  $A^i(0) = 0$ 

Thus the conjecture becomes

$$A^{i}(X) = c_{i}X \tag{32}$$

Plugging these expressions into the two ODEs characterizing the unlevered firm value and with some rearranging gives a linear system of two equations in two unknowns.

$$\mu_i c_i X - (\lambda_i + r) c_i X + X + \lambda_i c_j X = 0, \quad j \neq i$$
(33)

Solving these two equations for  $c_1, c_2$  gives the unlevered firm value in state i as:

$$A^{i}(X) = \frac{(\lambda_{1} + \lambda_{2} + r - \mu_{j})X}{\lambda_{2}(r - \mu_{1}) + (r - \mu_{2})(\lambda_{1} + r - \mu_{1})}$$
(34)

Note that if  $\mu_1 = \mu_2$  then the unlevered firm value is the same in both states and is given by

$$A(X) = \frac{X}{r - \mu} \tag{35}$$

### C Eigenvalue Problem

This section describes the eigenvalue problem for the cash flow region in which neither default nor restructuring are immediate threats. Define the log cash flow process,  $x_t = log(X_t)$ . By Itô's Lemma, under the risk-neutral measure, the log cash flow process evolves according to

$$dx_t = \left[\widehat{\mu}(\nu_t) - \frac{1}{2}\sigma_X(\nu_t)^2\right]dt + \sigma_X(\nu_t)d\widehat{W}_t$$

Under the risk-neutral measure, the price process of any contingent claim on firm cash flows will be a martingale with the cash flows discounted by investors at the risk-free short rate,  $r(\nu_t)$ . Thus, these contingent claims will be martingales of the form:

$$M_t^f = exp\left(-\int_0^t r(\nu_u) du\right) f(\nu_t, x_t)$$

for some function f that depends on the payoffs of the given security.

Applying Itô's Lemma gives

$$dM_t^f = exp\left(-\int_0^t r(\nu_u) \, du\right) \left[ (\Lambda - R)f + \frac{1}{2}\Sigma f_{xx} + \Theta f_x \right] dt$$

R is the diagonal matrix of  $r_i$ 's.  $\Sigma$  is the diagonal matrix of  $\sigma_{iX}^2$ 's.  $\Theta$  is the diagonal matrix of the risk-neutral drifts of the log cash flow process.  $\Lambda$  is the generator matrix of the Markov chain,  $\nu_t$ .

Since  ${\cal M}_t^f$  is a martingale, it has zero drift, implying

$$(\Lambda - R)f + \frac{1}{2}\Sigma f_{xx} + \Theta f_x = 0$$

We seek a separable f of the form

$$f(\nu_t, x_t) = g(\nu_t) exp(-\beta x_t) = g(\nu_t) X_t^{\beta}$$

This gives the following equation to be solved in  $\beta$  and g:

$$(\Lambda - R)g + \frac{1}{2}\beta^2 \Sigma g - \beta \Theta g = 0.$$

Premultiplying the above equation by  $2\Sigma^{-1}$  gives

$$2\Sigma^{-1}(\Lambda - R)g + \beta^2 g - 2\beta \Sigma^{-1}\Theta g = 0.$$

This gives the following system of equations:

$$\beta g = h$$

$$\beta h = 2\Sigma^{-1}\Theta h - 2\Sigma^{-1}(\Lambda - R)g$$

This can be written as a standard eigenvalue problem of the form

$$A\begin{pmatrix} g \\ h \end{pmatrix} = \begin{pmatrix} 0 & I \\ -2\Sigma^{-1}(\Lambda - R) & 2\Sigma^{-1}\Theta \end{pmatrix} \begin{pmatrix} g \\ h \end{pmatrix} = \beta \begin{pmatrix} g \\ h \end{pmatrix}$$
 (36)

If  $(g, \beta)$  solve this eigenvalue problem, then

$$M_t^f = exp\left(-\int_0^t r(\nu_u) du - \beta x_t\right) g(\nu_t)$$

is a martingale. The matrix A has exactly 2 eigenvalues with positive real parts and 2 with negative real parts.

## D Solving for the w coefficients

For the case in which there are two aggregate states to the Markov chain, there are a total of 3 relevant cash flow regions and each security has a total of 16 w coefficients (8 for each initial state).

The cash flow regions are:

Region 1:  $X \in [X_D^1, X_D^2)$ 

Region 2:  $X \in [X_D^2, X_U^{u(1)})$ 

Region 3:  $X \in [X_U^{u(1)}, X_U^{u(2)})$ 

Note that for  $X < X_D^1$  the firm is always in default regardless of the state and for  $X > X_U^{u(2)}$  the firm has already restructured upwards for any state.

### Debt

For a given initial state,  $\nu_0$ , the 8 boundary conditions for debt are

$$\lim_{X \uparrow X_D^2} D(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} D(X, 1, \nu_0)$$
 (37)

$$\lim_{X \uparrow X_D^2} D(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} D(X, 1, \nu_0)$$

$$\lim_{X \uparrow X_D^2} D_X(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} D_X(X, 1, \nu_0)$$
(38)

$$\lim_{X \uparrow X_U^{u(1)}} D(X, u(2), \nu_0) = \lim_{X \downarrow X_U^{u(1)}} D(X, u(2), \nu_0)$$
(39)

$$\lim_{X \uparrow X_U^{u(1)}} D(X, u(2), \nu_0) = \lim_{X \downarrow X_U^{u(1)}} D(X, u(2), \nu_0)$$

$$\lim_{X \uparrow X_U^{u(1)}} D_X(X, u(2), \nu_0) = \lim_{X \downarrow X_U^{u(1)}} D_X(X, u(2), \nu_0)$$

$$\underset{X \uparrow X_U^{u(1)}}{\text{(40)}}$$

$$D(X_D^1, 1, \nu_0) = (1 - \alpha(1))V^U(X_D^1, 1)$$
(41)

$$D(X_D^2, 2, \nu_0) = (1 - \alpha(2))V^U(X_D^2, 2)$$
(42)

$$D(X_U^{u(1)}, u(1), \nu_0) = D(X_0, \nu_0)$$
(43)

$$D(X_U^{u(2)}, u(2), \nu_0) = D(X_0, \nu_0)$$
(44)

Equations (37) and (39) are the value-matching conditions across cash flow regions and equations (38) and (40) are the smooth-pasting conditions across regions. Equations (43) and (44) are the value-matching boundary conditions for default and equations (43) and (44) are the value-matching boundary conditions for upward restructuring.

The initial (par value) of debt at time 0 is given by

$$D(X_0, \nu_0; \nu_0) = w_{2,1}^D(\nu_0)g_{2,1}(\nu_0)exp\{\beta_{2,1}x_0\} + w_{2,2}^D(\nu_0)g_{2,2}(\nu_0)exp\{\beta_{2,2}x_0\} + w_{2,3}^D(\nu_0)g_{2,3}(\nu_0)exp\{\beta_{2,3}x_0\} + w_{2,4}^D(\nu_0)g_{2,4}(\nu_0)exp\{\beta_{2,4}x_0\} + (1-\tau_i)C(\nu_0)\mathbf{b}(\nu_0)$$

$$D(X_0, \nu_0; \nu_0) = \sum_{j=1}^{4} w_{2,j}^D(\nu_0) g_{2,j}(\nu_0) exp\{\beta_{2,j} x_0\} + (1 - \tau_i) C(\nu_0) \mathbf{b}(\nu_0)$$
 (45)

Note that  $g_{2,j}(\nu_0)$  is a scalar: it's the  $\nu_0$  element of the  $g_{2,j}$  eigenvector, where  $g_{2,j}$  is the jth eigenvector for the eigenvalue problem for the 2nd cash flow region. Thus, we have a system of 8 equations to solve for the 8 unknown  $w^D$  coefficients.

$$G(X)_{LHS}W^D + \xi(X)_{LHS} + \zeta_{LHS} = G(X)_{RHS}W^D + \xi(X)_{RHS} + \zeta_{RHS}$$
  
 $[G(X)_{LHS} - G(X)_{RHS}]W^D = \xi(X)_{RHS} + \zeta_{RHS} - \xi(X)_{LHS} - \zeta_{LHS}$ 

Thus,

$$W^{D} = [G(X)_{LHS} - G(X)_{RHS}]^{-1} (\xi(X)_{RHS} + \zeta_{RHS} - \xi(X)_{LHS} - \zeta_{LHS})$$
(46)

### Equity

For a given initial state,  $\nu_0$ , the 8 boundary conditions for equity are

$$\lim_{X \uparrow X_D^2} E(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} E(X, 1, \nu_0) \tag{47}$$

$$\lim_{X \uparrow X_D^2} E(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} E(X, 1, \nu_0)$$

$$\lim_{X \uparrow X_D^2} E_X(X, 1, \nu_0) = \lim_{X \downarrow X_D^2} E_X(X, 1, \nu_0)$$
(48)

$$\lim_{X \uparrow X_U^{u(1)}} E(X, u(2), \nu_0) = \lim_{X \downarrow X_U^{u(1)}} E(X, u(2), \nu_0)$$
(49)

$$\lim_{X \uparrow X_U^{u(1)}} E_X(X, u(2), \nu_0) = \lim_{X \downarrow X_U^{u(1)}} E_X(X, u(2), \nu_0)$$
 (50)

$$E(X_D^1, 1, \nu_0) = 0 (51)$$

$$E(X_D^2, 2, \nu_0) = 0 (52)$$

$$E(X_U^{u(1)},u(1),\nu_0) \ = \ \frac{X_U^{u(1)}}{X_0}[(1-q)D(X_0,u(1);u(1)) + E(X_0,u(1);u(1))] - D(X_0,\nu_0;\iota_0^*)$$

$$E(X_U^{u(2)}, u(2), \nu_0) = \frac{X_U^{u(2)}}{X_0} [(1-q)D(X_0, u(2); u(2)) + E(X_0, u(2); u(2))] - D(X_0, \nu_0; \iota_0^*)$$

Note that these conditions hold for an arbitrary coupon rate,  $C(\nu_0)$ . For a given initial state,  $\nu_0$ , the optimal default thresholds (for an arbitrary coupon) satisfy the smooth-pasting conditions for equity such that

$$\left. \frac{\partial}{\partial X} E(X, 1; \nu_0) \right|_{X \downarrow X_D^1(\nu_0)} = 0 \tag{55}$$

$$\frac{\partial}{\partial X} E(X, 1; \nu_0) \Big|_{X \downarrow X_D^1(\nu_0)} = 0$$

$$\frac{\partial}{\partial X} E(X, 2; \nu_0) \Big|_{X \downarrow X_D^2(\nu_0)} = 0$$
(55)

### E Data

### **Aggregate Earnings**

For the aggregate earnings series, I use the quarterly "Net Operating Surplus" series from NIPA Section 1, Table 1.14, Line 8. The quarterly series is available for the period 1947Q1-2010Q2. I construct the log earnings growth series and present summary statistics for the unconditional moments below (all values are quarterly).

Unconditional Moments:	Quarterly Aggregate Earnings Growth
Mean	0.017
Std Dev	0.053
AC(1)	0.111

#### Firm Data

I construct the sample of firms to be estimated from the Compustat Fundamentals Quarterly file merged with equity data from CRSP. I require firms to have at least 20 quarters of data in the Compustat and CRSP files.

Variable definitions:

- Book Leverage:  $\frac{\text{dlccq} + \text{dlttq}}{\text{atq}}$
- Earnings Growth:

$$\widetilde{e}_{t+1} = \frac{\sum_{j=0}^{K} e_{t+1-j}}{\sum_{j=0}^{K} e_{t-j}} - 1$$

where  $e_t$  is Compustat item 'oiadpq' in quarter t.

• Quasi-Market Leverage:  $\frac{\text{dlccq} + \text{dlttq}}{\text{dlccq} + \text{dlttq} + \text{ME}}$  where ME is constructed from CRSP as Price\*(Shares Outstanding).

# F Estimating Parameters of the Aggregate Earnings Process

The procedure I use to estimate the parameters of the aggregate earnings growth follows the exposition in Chapter 22 of Hamilton (1994) on estimating Markov chain regime-switching

processes. See also Hamilton (1989). In the model, aggregate earnings is assumed to evolve according to a Markov-modulated geometric Brownian motion:

$$\frac{dX_t^A}{X_t^A} = \mu^A(\nu_t)dt + \sigma^A(\nu_t)dW_t^A. \tag{57}$$

By Itô's Lemma, the quarterly log earnings growth rate,  $x_{t+1}$ , can be written as

$$x_{t+1} \equiv \Delta log(X_{t+1}) = \mu^{A}(\nu_t) - \frac{1}{2}\sigma^{A}(\nu_t) + \varepsilon_{t+1}^{A}$$
 (58)

where  $\varepsilon_{t+1}^A \sim \mathcal{N}(0, (\sigma^A(\nu_t))^2)$ .

This gives six parameters to be estimated:  $\mu_1^A, \mu_2^A, \sigma_1^A, \sigma_2^A, \lambda_{12}$ , and  $\lambda_{21}$ . Stacking these parameters into a vector,  $\Theta$ , the vector of conditional densities for each state can be expressed as

$$\eta_{t} = \begin{bmatrix} f(x_{t}|\nu_{t-1} = 1, x_{t-1}; \Theta) \\ f(x_{t}|\nu_{t-1} = 2, x_{t-1}; \Theta) \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2\pi}\sigma_{1}^{A}} exp \begin{cases} \frac{-(x_{t}-\mu_{1}^{A} + \frac{1}{2}(\sigma_{1}^{A}))^{2}}{2(\sigma_{1}^{A})^{2}} \\ \frac{1}{\sqrt{2\pi}\sigma_{2}^{A}} exp \begin{cases} \frac{-(x_{t}-\mu_{1}^{A} + \frac{1}{2}(\sigma_{1}^{A}))^{2}}{2(\sigma_{2}^{A})^{2}} \end{cases} \end{bmatrix}$$
 (59)

Define the vector of optimal inferences for the current state at date t, given the vector of observations up to and including date t,  $\mathcal{X}_t$ , and the vector of population parameters,  $\Theta$ , as

$$\hat{\xi}_{t|t} = \begin{bmatrix} \mathbb{P}\{\nu_t = 1 | \mathcal{X}_t; \Theta\} \\ \mathbb{P}\{\nu_t = 2 | \mathcal{X}_t; \Theta\} \end{bmatrix}$$
(60)

Similarly, define the vector of optimal one period ahead forecasts for state  $\nu_{t+1}$  as

$$\hat{\xi}_{t+1|t} = \begin{bmatrix} \mathbb{P}\{\nu_{t+1} = 1 | \mathcal{X}_t; \Theta\} \\ \mathbb{P}\{\nu_{t+1} = 2 | \mathcal{X}_t; \Theta\} \end{bmatrix}$$
(61)

The optimal inference and forecast can be defined recursively as

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t|t-1} \odot \eta_t}{\mathbf{1}'(\hat{\xi}_{t|t-1} \odot \eta_t)} \tag{62}$$

$$\hat{\xi}_{t+1|t} = P'\hat{\xi}_{t|t} \tag{63}$$

where  $\odot$  denotes element by element multiplication and P is the discrete time transition matrix given by

$$P = \left[ \begin{array}{cc} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{array} \right]$$

Starting with an initial guess for  $\xi_{1|0}$  equal to the vector of unconditional probabilities and a vector of parameters,  $\Theta$ , the log likelihood function can be constructed by iterating on equations (62) and (63).

$$\mathcal{L}(\Theta) = \sum_{t=1}^{T} log f(x_t | \mathcal{X}_{t-1}; \Theta) = \sum_{t=1}^{T} log(\mathbf{1}'(\hat{\xi}_{t|t-1} \odot \eta_t))$$
(64)

To estimate the parameter vector  $\Theta$ , I maximize the log likelihood function given in (64) numerically. Finally, given the estimated discrete time transition matrix, P, the generator matrix,  $\Lambda$ , for the continuous time Markov chain can be computed as<sup>27</sup>

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} = \begin{bmatrix} log(p_{11}) & \frac{(1-p_{11})log(p_{11})}{p_{11}-1} \\ \frac{(1-p_{22})log(p_{22})}{p_{22}-1} & log(p_{22}) \end{bmatrix}$$
(65)

<sup>&</sup>lt;sup>27</sup>Note that this assumes that the probability of switching states more than once in a quarter is zero. See Jarrow, Lando, and Turnbull (1997) for more details.