Credit and Option Risk Premia*

Lars-Alexander Kuehn
Tepper School of Business
Carnegie Mellon University

David Schreindorfer
W.P. Carey School of Business
Arizona State University

Florian Schulz
Michael G. Foster School of Business
University of Washington

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Abstract

The goal of this paper is to extract the joint distribution of default probabilities and recover rates from the prices of credit default swaps and equity options. To this end, we estimate a structural model of credit risk with a representative agent with recursive preferences and Markov-switching states for the drift and volatility of consumption and earnings growth. While CDS prices are sensitive to both the (risk-neutral) firm-specific default probability and loss rates for bond holders, equity option prices are only sensitive to the default probability because equity holders recovery very little in bankruptcy. Using the information in both CDS rates and put option prices, we can recover default probabilities, recovery rates, and bankruptcy costs.

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1 Introduction

The value of a corporate debt claim depends on the likelihood that the firm's assets are worth less than the face value of debt, i.e., the probability of default, as well as the losses of bondholders in default, i.e., loss given default rates. In most calibration and estimation exercises of credit risk models, the time variation in default probabilities is accounted for, but loss rates are assumed constant and set at long-run historical averages.

The goal of this paper is to extract the joint distribution of default probabilities and recovery rates from the prices of credit default swaps and equity options. To this end, we estimate a structural model of credit risk with a representative agent with recursive preferences and Markov-switching states for the drift and volatility of aggregate consumption and firm level earnings growth. The resulting pricing kernel is calibrated to match the aggregate equity and option market moments. Firms issue debt, refinance when the interest coverage ratio is too high, and optimally default when the interest coverage ratio is too low. The dynamics of debt and equity prices also allows us to value derivative securities written on them.

Using firm-level data on CDS rates and put option prices, we estimate firm-level earnings and costs parameters. While CDS prices are sensitive to both the (risk-neutral) firm-specific default probability and loss rates for bond holders, equity option prices are only sensitive to the default probability because equity holders recovery very little in bankruptcy. Using the information in both CDS rates and put option prices, we can then recover default probabilities, recovery rates, and bankruptcy costs.

While it is well-known that recovery rates are procyclical, estimates of default probabilities based on credit risk models typically ignore this channel. As a consequence, estimates of default probabilities tend to be upward biased in recessions and downward biased in expansions. Our separation into time-variation in default probabilities and time-variation in recovery rates allows us to remove this bias and should therefore lead to a better estimate of firms' conditional default probabilities. We will test this prediction by evaluating the performance of our estimates in hazard models and out-of-sample forecasts, and benchmark it against predictors of firm default suggested in the previous literature. Barath and Shumway (2008) perform a similar analysis for the distance-to-default measure inferred from the Merton (1974) model.

Our work is also related to that of Glover (2016), who argues that the sample of observed defaults significantly understates the average firm's true expected cost of default due to a sample selection bias. Firms with higher cost of default endogenously opt for a lower level of leverage, and thus default at lower frequency all else equal. Glover argues that the negative correlation between the probability of default and loss rates causes a downward bias in the expected cost of default based on average observed defaults. By disentangling loss rates and default probabilities, our study can also empirically address the validity of this channel.

2 Model

The goal of the model is capture the joint price dynamics of credit default swaps and options written on individual firms. To this end, we assume an representative investor with recursive preferences and consumption dynamics with Markov switching drift and volatility. It is well-known that these assumptions generate time-varying aggregate risk premia. At the firm level, firms choose optimal capital structure. Firms issue perpetual debt, trading off tax shields and bankruptcy costs. After a sequence of positive earnings news, firms optimally issue more debt and after a sequence of negative earnings news, firms optimally default.

2.1 Pricing Kernel

To allow risk premia to fluctuate with macroeconomic conditions, we follow the consumption-based asset pricing literature and model the pricing kernel as the marginal utility of consumption of a representative investor. Specifically, log aggregate consumption growth $g_{c,t+1}$ follows a Markov-switching modulated random walk

$$g_{c,t+1} = \mu_{c,t} + \sigma_{c,t}\varepsilon_{c,t+1}, \tag{1}$$

where the conditional mean $\mu_{c,t}$ and volatility $\sigma_{c,t}$ of consumption growth depend on the aggregate Markov state ξ_t, and $\varepsilon_{c,t+1}$ are standard normal innovations. The aggregate state ξ_t follows a Markov chain with transition matrix $\mathcal{P}$.

The representative agent has recursive preferences over consumption C_t such that her utility function U_t solves

$$U_t = \left\{(1-\beta)C_t^{\rho} + \beta\mathbb{E}_t[U_{t+1}^{\alpha}]^{\rho/\alpha}\right\}^{1/\rho}, \tag{2}$$

where β is the time discount rate, $\alpha = 1-\gamma$ measures risk aversion γ and $\rho = 1/(1-\psi)$ the elasticity of intertemporal substitution (EIS) ψ.

The implied pricing kernel expressed in terms of the wealth-consumption ratio, $\lambda_t^c = W_t/C_t$, which is a function of the aggregate state ξ_t, $\lambda^c(\xi_t)$, reads

$$M_{t,t+1} = \beta^\theta \left(\frac{\lambda_{t+1}^c + 1}{\lambda_t^c}\right)^{-(1-\theta)} \left(\frac{C_{t+1}}{C_t}\right)^{\alpha-1} = \beta^\theta \left(\frac{\lambda_{t+1}^c + 1}{\lambda_t^c}\right)^{-(1-\theta)} e^{-\gamma g_{c,t+1}}, \tag{3}$$

where $\theta = \frac{\alpha}{\rho}$. The wealth-consumption ratio solves the Euler equation

$$(\lambda_t^c)^\theta = \beta^\theta \mathbb{E}_t\left[\left(\lambda_{t+1}^c + 1\right)^\theta \left(\frac{C_{t+1}}{C_t}\right)^{1-\gamma}\right] = \beta^\theta e^{\alpha\mu_{c,t}+\frac{1}{2}\alpha^2\sigma_{c,t}^2}\mathbb{E}_t\left[\left(\lambda_{t+1}^c + 1\right)^\theta\right]. \tag{4}$$

2.2 Unlevered Firm Value

Firm i's earnings before interest and taxes (EBIT) $E_{i,t}$ are exogenous and follow a Markov-switching modulated random walk, whose growth rate moments depend on the aggregate Markov state ξ_t. Specifically, log earnings growth $g_{i,t+1}$ follows

$$g_{i,t+1} = \mu_{i,t} + \sigma_{i,t}\varepsilon_{t+1} + \zeta_i \nu_{i,t+1}, \tag{5}$$

where the conditional mean $\mu_{i,t}$ and systematic volatility $\sigma_{i,t}$ depend on the aggregate state ξ_t, ε_{t+1} are systematic standard normal innovations with correlation ρ_i with the aggregate Gaussian shock $\varepsilon_{c,t+1}$, ζ_i is idiosyncratic volatility, and $\nu_{i,t+1}$ are idiosyncratic standard normal innovations, uncorrelated with the aggregate Gaussian shock.

The unlevered firm value is the present value of after-tax earnings. The corporate income tax rate is η and provides a motive for firms to issue defaultable debt. The after-tax cum-earnings asset value $A_{i,t}$ is given by

$$A_{i,t} = (1-\eta)E_{i,t} + \mathbb{E}_t[M_{t,t+1}A_{i,t+1}]. \tag{6}$$

Since earnings grow exponentially, we detrend all valuation equations by earnings and solve for stationary valuations ratios, such as the cum-earnings asset-earnings ratio, $\lambda_{i,t}^a = A_{i,t}/E_{i,t}$,

$$\lambda_i^a(\xi_t) = 1 - \eta + \mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda_i^a(\xi_{t+1})], \tag{7}$$

which depends on the aggregate state ξ_t.

2.3 Debt Value

Firms can issue perpetual debt to take advantage of the tax benefits of debt financing. Optimally leverage is determined as the trade off between tax shields and bankruptcy costs. In addition, firms can issue more debt in the future or declare default.

The interest coverage ratio $\kappa_{i,t}$ is defined as the ratio of current earnings $E_{i,t}$ to coupon $c_{i,s}$ based on the most recent debt issuance date s

$$\kappa_{i,t} = \frac{E_{i,t}}{c_{i,s}}.$$

When firms are hit by a sequence of negative earning shocks, earnings might not be sufficient to cover interest expenses. Eventually, the interest coverage ratio falls below the aggregate state dependent threshold $\kappa_{i,t}^D = \kappa_i^D(\xi_t)$ and equity holders optimally declare default.

In the opposite case, firms receive a sequence of positive earnings news and the interest coverage ratio rises. A rising interest coverage ratio also implies lower leverage and a shrinking benefit of tax shields. Consequently, when the interest coverage ratio exceeds the aggregate state dependent threshold $\kappa_{i,t}^I = \kappa_i^I(\xi_t)$, firms issue more debt such that the interest coverage ratio resets to the optimal state dependent interest coverage ratio $\bar{\kappa}_{i,t} = \bar{\kappa}_i(\xi_t) = \frac{E_{i,t}}{c_{i,t}}$. Importantly, firms do not refinance every period because of proportional debt issuance costs. Both issuance and optimal interest coverage ratios are set to maximize total firm value.

Given these dynamics, the cum-coupon debt value is given by

$$\begin{aligned} D_{i,t} &= 1_{\{\kappa_{i,t} \le \kappa_{i,t}^D\}}(1-\omega_{i,t})A_{i,t} \\ &+ 1_{\{\kappa_{i,t}^D < \kappa_{i,t} < \kappa_{i,t}^I\}}\big(c_{i,s} + \mathbb{E}_t[M_{t,t+1}D_{i,t+1}]\big) \\ &+ 1_{\{\kappa_{i,t}^I \le \kappa_{i,t}\}}\left(c_{i,s} + \frac{c_{i,s}}{c_{i,t}}\mathbb{E}_t[M_{t,t+1}D_{i,t+1}]\right), \end{aligned} \tag{8}$$

where $\omega_{i,t}$ are aggregate state dependent bankruptcy costs. The first term captures the cash-flows in default when $\kappa_{i,t} \le \kappa_{i,t}^D$. When the interest coverage ratio varies between the default and issuance thresholds, $\kappa_{i,t}^D < \kappa_{i,t} < \kappa_{i,t}^I$, firms optimally do not adjust their capital structure and pay coupon $c_{i,s}$ in perpetuity, as described by the second term. The last term captures debt value when firms issue additional debt in case the interest coverage ratio exceeds the issuance threshold, $\kappa_{i,t}^I \le \kappa_{i,t}$. When new debt is issued at date t, coupon payments increase from $c_{i,s}$ to $c_{i,t}$. While current bond holders are entitled to coupon payments $c_{i,s}$ in perpetuity, they also receive the fraction $\frac{c_{i,s}}{c_{i,t}}$ of the new bond's value, $\mathbb{E}_t[M_{t+1}D_{i,t+1}]$.

As the debt value trends with earnings, we solve for the stationary cum-coupon debt-earnings ratio, $\lambda^d_{i,t} = D_{i,t}/E_{i,t}$,

$$\begin{aligned}\lambda_i^d(\kappa_{i,t},\xi_t) &= 1_{\{\kappa_{i,t}\leq\kappa^D_{i,t}\}}(1-\omega_{i,t})\lambda_i^a(\xi_t) \\ &+ 1_{\{\kappa^D_{i,t}<\kappa_{i,t}<\kappa^I_{i,t}\}}\left(\frac{1}{\kappa_{i,t}} + \mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda_i^d(\kappa_{i,t}e^{g_{i,t+1}},\xi_{t+1})]\right) \\ &+ 1_{\{\kappa^I_{i,t}\leq\kappa_{i,t}\}}\left(\frac{1}{\kappa_{i,t}} + \frac{\bar{\kappa}_{i,t}}{\kappa_{i,t}}\mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda_i^d(\bar{\kappa}_{i,t}e^{g_{i,t+1}},\xi_{t+1})]\right),\end{aligned} \tag{9}$$

which depends on the firm's interest coverage ratio and aggregate state. Given default, issuance, and leverage ratios, this fixed point equations is well defined. Next, we solve for the optimal ratios.

To model the time-variation in bankruptcy costs, we assume a logistic function such that

$$\omega_{i,t} = \frac{\bar{\omega}}{1+e^{(\mu_{c,t}/\sigma_{c,t}-a)b}}, \tag{10}$$

where $\bar{\omega}$ controls the maximum, a the level, and b the sensitivity of bankruptcy costs. Bankruptcy costs should be higher when the conditional mean of consumption growth $\mu_{c,t}$ is low or when the conditional volatility of consumption growth $\sigma_{c,t}$ is high, requiring that the coefficient b is positive.

2.4 Equity Value

Equity holders decide about the optimal timing of default by maximizing the cum-dividend equity value $S_{i,t}$

$$\begin{aligned}S_{i,t} &= \max\Big\{0, 1_{\{\kappa_{i,t}<\kappa^I_{i,t}\}}\big((1-\eta)(E_{i,t}-c_{i,s}) + \psi_e(E_{i,t}-c_{i,s})1_{\{E_{i,t}<c_{i,s}\}} + \mathbb{E}_t[M_{t,t+1}S_{i,t+1}]\big) \\ &+ 1_{\{\kappa^I_{i,t}\leq\kappa_{i,t}\}}\big((1-\eta)(E_{i,t}-c_{i,s}) + (1-\psi_d)(D_{i,t}(c_{i,t})-c_{i,t}) - (D_{i,t}(c_{i,s})-c_{i,s}) \\ &+ \mathbb{E}_t[M_{t,t+1}S_{i,t+1}]\big)\Big\}.\end{aligned} \tag{11}$$

Intuitively, when the interest coverage ratio is less than the issuance thresholds, $\kappa_{i,t} < \kappa^I_{i,t}$, firms pay after-tax dividends of $(1-\eta)(E_{i,t}-c_{i,s})$. However, when earnings are not sufficient to cover interest expenses, $E_{i,t} < c_{i,s}$, the firm has to raise equity which trigger equity issuance costs ψ_e. When the present value of after-tax dividends is less than zero, equity holders declare default and the equity value drops to zero, which is captured by the first term in the max-operator. When the interest coverage ratio rises and exceeds the issuance threshold, $\kappa^I_{i,t} \leq \kappa_{i,t}$, firms lever up and equity holders receive a special dividend in the amount of the ex-coupon price of newly issued debt, $D_{i,t}(c_{i,t})-c_{i,t}$, net of debt issuance costs ψ_d and existing bond holder ex-coupon value, $D_{i,t}(c_{i,s}) - c_{i,s}$.

As the equity value trends with earnings, we solve for the stationary cum-dividend equity-earnings ratio, $\lambda^s_{i,t} = S_{i,t}/E_{i,t}$,

$$\begin{aligned} \lambda^s_i(\kappa_{i,t}, \xi_t) &= \max\Bigg\{0, 1_{\{\kappa_{i,t}<\kappa^I_{i,t}\}}\Bigg((1-\eta)\left(1-\frac{1}{\kappa_{i,t}}\right) + \psi_e\left(1-\frac{1}{\kappa_{i,t}}\right)1_{\{\kappa_{i,t}<1\}} \\ &+ \mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda^s_i(\kappa_{i,t}e^{g_{i,t+1}}, \xi_{t+1})]\Bigg) \\ &+ 1_{\{\kappa^I_{i,t}\leq\kappa_{i,t}\}}\Bigg((1-\eta)\left(1-\frac{1}{\kappa_{i,t}}\right) + \left(1-\psi_d-\frac{\bar{\kappa}_{i,t}}{\kappa_{i,t}}\right)\lambda^{d,ex}_i(\bar{\kappa}_{i,t}, \xi_t) \\ &+ \mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda^s_i(\bar{\kappa}_{i,t}e^{g_{i,t+1}}, \xi_{t+1})]\Bigg)\Bigg\}, \end{aligned} \tag{12}$$

which depends on the firm's interest coverage ratio and aggregate state. Given the cum-dividend equity-earnings ratio, the optimal state depend default threshold satisfies

$$\kappa^D_i(\xi_t) = \max\{\kappa_{i,t} : \lambda^s_i(\kappa_{i,t}, \xi_t) \leq 0\}. \tag{13}$$

Equity holders declare default when the interest coverage ratio falls below this default trigger.

2.5 Levered Firm Value

Levered firm value is the sum of the value of debt and equity. Management chooses the optimal issuance threshold $\kappa^I_{i,t}$ and the optimal coverage ratio $\bar{\kappa}_{i,t}$ to maximize the cum cash flow firm value.

In stationary terms, the levered firm value to earnings ratio, $\lambda^f_{i,t}$, is given by

$$\begin{aligned}
\lambda^f_i(\kappa_{i,t},\xi_t) &= 1_{\{\kappa_{i,t}\le\kappa^D_{i,t}\}}(1-\omega_{i,t})\lambda^a_i(\xi_t) \\
&+ 1_{\{\kappa^D_{i,t}<\kappa_{i,t}<\kappa^I_{i,t}\}}\left(1-\eta+\frac{\eta}{\kappa_{i,t}}+\psi_e\left(1-\frac{1}{\kappa_{i,t}}\right)1_{\{\kappa_{i,t}<1\}}\right. \\
&+ \left.\mathbb{E}_t\big[M_{t,t+1}e^{g_{i,t+1}}\lambda^f_i(\kappa_{i,t}e^{g_{i,t+1}},\xi_{t+1})\big]\right) \qquad (14)\\
&+ 1_{\{\kappa^I_{i,t}\le\kappa_{i,t}\}}\left(1-\eta+\frac{\eta}{\kappa_{i,t}}-\psi_d\lambda^{d,ex}_i(\bar\kappa_{i,t},\xi_t)+\mathbb{E}_t\big[M_{t,t+1}e^{g_{i,t+1}}\lambda^f_i(\bar\kappa_{i,t}e^{g_{i,t+1}},\xi_{t+1})\big]\right).
\end{aligned}$$

Intuitively, in the case of default, when the interest coverage ratio drops below the default threshold, $\kappa_{i,t}\le\kappa^D_{i,t}$, bond holders recover the fraction $1-\omega$ of asset value. When the interest coverage ratio varies between the default and issuance thresholds, $\kappa^D_{i,t}<\kappa_{i,t}<\kappa^I_{i,t}$, firms optimally do not adjust their capital structure and cash-flows equal after-tax earnings $1-\eta$ plus tax shields in the amount $\eta/\kappa_{i,t}$. When the interest coverage ratio exceeds the issuance threshold, $\kappa^I_{i,t}\le\kappa_{i,t}$, firms issue additional debt and cash-flows equal after-tax earnings $1-\eta$ plus tax shields $\eta/\kappa_{i,t}$ net off issuance costs $\psi_d\lambda^{d,ex}_{i,t}$.

Maximizing firm value implies that the state dependent optimal interest coverage ratio is given by

$$\bar\kappa_i(\xi_t)=\arg\max_{\kappa}\Big\{-\psi\lambda^{d,ex}_i(\kappa,\xi_t)+\mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda^f_i(\kappa e^{g_{i,t+1}},\xi_{t+1})]\Big\} \qquad (15)$$

which captures the marginal issuance costs and future tax benefit trade off. Similarly, the state dependent optimal issuance threshold is given by the interest coverage ratio when the firm continuation value of issuance dominantes the one without issuance

$$\kappa^I_i(\xi_t)=\min\{\kappa_{i,t}:\mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda^f_i(\bar\kappa_{i,t}e^{g_{i,t+1}},\xi_{t+1})]\ge\mathbb{E}_t[M_{t,t+1}e^{g_{i,t+1}}\lambda^f_i(\kappa_{i,t}e^{g_{i,t+1}},\xi_{t+1})]\}.$$

2.6 Credit Default Swaps

Given the price dynamics of debt and equity, we are now equipped to price derivative securities written on them. In this section, we tackle the pricing of credit default swaps and in the following section the pricing of put option contracts. We first derive a closed-form expression for the one-period CDS contract, which we then extended to any horizon.

2.6.1 One-Period Contract

Firm i defaults at time τ_i when its interest coverage ratio $\kappa_{i,t}$ drops below the default threshold $\kappa_{i,t}^D$ such that

$$\tau_i = \inf\{t : \kappa_{i,t} \leq \kappa_{i,t}^D\}. \tag{16}$$

The one-period CDS rate z^1 equates the present value of the payments made by the insurance seller and the insurance buyer. The insurance seller receives the CDS rate tomorrow in the case of no default. The value of its claim is

$$z^1(\kappa_{i,t}, \xi_s, \xi_t)\mathbb{E}_t\left[M_{t,t+1}(1 - 1_{\{\tau_i = t+1\}})\right].$$

In the case of default tomorrow, the insurance seller has to payout the loss rate x to the insurance buyer, which are the after-tax firm value net of bankruptcy costs, $(1 - \omega_{t+1})A_{i,t+1}$, relative to their initial investment, $D_{i,s}$, and given by

$$x_{i,t+1,s} = 1 - \frac{(1 - \omega_{i,t+1})A_{i,t+1}}{D_{i,s}}.$$

The value of the insurance buyer's claim is

$$\mathbb{E}_t\left[M_{t,t+1}1_{\{\tau_i = t+1\}}L_{i,t+1,s}\right].$$

By equating these to values and changing measure, the one-period CDS rate z^1 is given by

$$z^1(\kappa_{i,t}, \xi_s, \xi_t) = \frac{\mathbb{E}_t^{\mathbb{Q}}\left[1_{\{\tau_i = t+1\}}x_{i,t+1,s}\right]}{1 - \mathbb{E}_t^{\mathbb{Q}}\left[1_{\{\tau_i = t+1\}}\right]}, \tag{17}$$

which depends on the firm's interest coverage ratio $\kappa_{i,t}$, the most recent debt issuance state ξ_s, the aggregate state ξ_t, and loss rates to bond holders $L_{i,t+1,s}$. We further define the risk-neutral one-period default probability by

$$q_{i,t}^1 = \mathbb{E}_t^{\mathbb{Q}}\left[1_{\{\tau_i = t+1\}}\right] \tag{18}$$

and the risk-neutral loss rate given default

$$L_{i,t,s}^{\mathbb{Q}} = \mathbb{E}_t^{\mathbb{Q}}\big[x_{i,t+1,s}|\tau_i = t+1\big]. \tag{19}$$

Given these definition, the CDS rate can be written as

$$z^1(\kappa_{i,t}, \xi_s, \xi_t) = \frac{\mathbb{E}_t^{\mathbb{Q}}\left[L_{i,t+1,s}|\tau_i = t+1\right]\mathbb{E}_t^{\mathbb{Q}}\left[1_{\{\tau_i = t+1\}}\right]}{1 - \mathbb{E}_t^{\mathbb{Q}}\left[1_{\{\tau_i = t+1\}}\right]}, \tag{20}$$

and the log CDS rate can be approximated by

$$\ln(z^1_{i,s,t}) \approx \ln(q^1_{i,t}) + \ln(L^{\mathbb{Q}}_{i,t,s}). \tag{21}$$

This approximation illustrates that credit spreads are zero if default does not occur in expectations, implying that both terms are zero. In contrast, credit spreads increase in the risk-neutral default probability and loss rate.

Since the underlying asset for CDS contracts are bonds, CDS contracts are sensitive to both the term structure of risk-neutral default probabilities as as well as to risk-neutral loss rates. Since risk-neutral loss rates are not observable without an economic model, most reduced form credit risk models are calibrated to average actual loss rates. The contribution of this paper is to disentangle the variation of credit spreads into the variation of default risk and loss rates. To this end, we use the market information of put option prices. Since equity holders recovery close to nothing in the case of default, put option contracts are only sensitive to the risk of default.

To see this intuition more clearly, we compute the variance of the log-linearized one-period CDS rate

$$\mathrm{Var}(\ln(z^1_{i,s,t})) = \mathrm{Var}(\ln(q^1_{i,t})) + \mathrm{Var}(\ln(L^{\mathbb{Q}}_{i,t,s})) + 2\mathrm{Cov}(\ln(q^1_{i,t}), \ln(L^{\mathbb{Q}}_{i,t,s})). \tag{22}$$

While most reduced form credit risk models assign all variation of credit spreads to risk-neutral default probabilities because of constant loss rates, we use put prices to measure the volatility of default probabilities. Given the observed variance of CDS rates, we can then estimate the variance of loss rates.

Given the Gaussian-Markov switching environment, we can derive a closed-form expression for both the risk-neutral default probability as well as the risk-neutral loss rate. This step facilitates the structural estimation of the model because we do not have to rely on Monte-Carlo pricing for CDS rates. More specifically, the risk-neutral one-period default probability is given by

$$q^1_{i,t} = \mathbb{E}^{\mathbb{Q}}_t[\Phi(a_{i,t+1})] \qquad a_{i,t+1} = \frac{\log\left(\frac{\kappa^D_{i,t+1}}{\kappa_{i,t}}\right) - \mu^{\mathbb{Q}}_{i,t}}{\bar{\sigma}_{i,t}} \tag{23}$$

where $a_{i,t+1}$ is the negative of the distance-to-default and $\bar{\sigma}_{i,t}$ is total asset volatility.

2.6.2 Multi-Period Contract

More generally, the no-arbitrage monthly CDS rate z^T for horizon T equates the present value of the payments made by the insurance seller and the insurance buyer and is given by

$$z^T(\kappa_{i,t}, \xi_s, \xi_t) = \frac{\sum_{h=1}^{T} \mathbb{E}_t^{\mathbb{Q}} \left[1_{\{\tau_i = t+h\}} x_{i,t+h,s}\right] / R_{t,t+h}^f}{\sum_{h=1}^{T} (1 - \mathbb{E}_t^{\mathbb{Q}} \left[1_{\{\tau_i \leq t+h\}}\right]) / R_{t,t+h}^f}, \tag{24}$$

which depends on the firm's interest coverage ratio $\kappa_{i,t}$, the most recent debt issuance state ξ_s, the aggregate state ξ_t, and loss rates to bond holders L. In the case of default, bond holders take over the firm recover the after-tax firm value net of bankruptcy costs, $(1 - \omega_{i,t+h})A_{i,t+h}$, such that their losses are relative to their initial investment, $D_{i,s}$, and given by

$$x_{i,t+h,s} = 1 - \frac{(1 - \omega_{i,t+h})A_{i,t+h}}{D_{i,s}} = 1 - \frac{(1 - \omega_{t+h})\lambda_{i,t+h}^a}{\lambda_i^d(\bar{\kappa}_{i,s}, \xi_s)} \frac{\kappa_{i,t+h}}{\bar{\kappa}_{i,s}}. \tag{25}$$

The pricing of multi-period CDS contracts requires the h-period ahead conditional default probability given by

$$q_{i,t}^h = \mathbb{E}_t^{\mathbb{Q}} \left[1_{\{\tau_i = t+h\}}\right]. \tag{26}$$

By the law of iterated expectation, this probability can be computed recursively

$$q_{i,t}^h = \mathbb{E}_t^{\mathbb{Q}} \left[q_{i,t+1}^{h-1}\right],$$

starting with the one-period probability (23). The risk-neutral h-period ahead default probability can be further decomposed into the actual default probability, $p_{i,t}^h$, and a risk adjustment, measured by a covariance with the pricing kernel, such that

$$q_{i,t}^h = p_{i,t}^h + \mathrm{Cov}_t\left(\frac{M_{t,t+h}}{\mathbb{E}[M_{t,t+h}]}, 1_{\{\tau_i = t+h\}}\right). \tag{27}$$

Since defaults tend to cluster in recessions when marginal utility is high, this covariance is positive. Consequently, credit spreads are high if the risk compensation and actual default probabilities are high. Similarly, the risk-neutral loss rate given default can be decomposed into the average loss rate under the physically measure, which is observable in the data, and a risk compensation, measured by a covariance with the pricing kernel, such that

$$L_{i,s,t}^{\mathbb{Q}} = L_{i,s,t} + \mathrm{Cov}_t\left(\frac{M_{t,t+1}}{\mathbb{E}[M_{t,t+1}]}, x_{i,t+1,s} | 1_{\{\tau_i = t+1\}}\right). \tag{28}$$

Since marginal utility is countercyclical in our model and loss rates tend to be countercyclical, the covariance is positive. Thus, credit spreads are large if our model endogenously generates countercyclical loss rates.

2.7 Equity Option Pricing

The value of a European put option with maturity T and strike price X is given by

$$P_{i,t} = \mathbb{E}_t[M_{t,T} \max\{X - S_{i,T}, 0\}]. \tag{29}$$

The put price-earnings ratio $\lambda^p_{i,t} = P_{i,t}/E_{i,t}$ solves

$$\lambda^p_{i,t} = \mathbb{E}_t[M_{t,T} \max\{\lambda^s_{i,t} K - e^{g_{i,t+1}+\ldots+g_{i,T}} \lambda^{s,ex}_{i,T}, 0\}], \tag{30}$$

where $K = X/S_{i,t}$ is the option moneyness and $\lambda^{s,ex}_{i,T}$ is the ex-dividend price-earnings ratio. Because the Black-Scholes-Merton formula is homogeneous of degree zero in the spot price of the underlying and the strike price, implied volatilities can then be found based on $\lambda^p_{i,t}$ and K.

3 Empirics

3.1 Firm Level Moments

The data used in the empirical section of this paper are collected from a number a sources.

Daily data on credit default swaps (CDS) for a large sample of debt issuers are obtained from *Credit Market Analysis Ltd.* (CMA) for the period from January 2004 to August 2014. The CMA dataset has information on pricing (bid and ask quotes) and contract terms of the underlying debt and credit default swaps (e.g., currency, debt seniority, credit event of restructuring, and tenor of the CDS contract). Mayordomo, Pena, and Schwartz (2010) find that the CMA database leads the price discovery process in comparison with other CDS databases including Markit. We focus on five-year credit spreads, which tend to be the most liquid, and spreads for the shorter tenor of one year.

As our interest is on the joint behavior of prices of CDS contracts and equity options, we also require that equity options are available. We therefore focus our analysis on constituents of the S&P 100 index, an index of blue chip companies across multiple industry groups, which ensures that individual stock options are listed for each index constituent.

Equity option data are obtained from *OptionMetrics*, which provides end-of-day bid and ask quotes on traded put and call options as well as implied volatilities (IV) on a number of contracts standardized across maturity and moneyness (implied volatility surface). Individual equity options are American style, and OptionMetrics uses binomial trees to compute implied volatilities that account for early exercise. For the majority of our analysis, we focus on the latter implied volatility surface data as it provides a relatively stable number of contracts and allows a more homogenous analysis across firms than would be the case with the traded option quotes.

For the subset of firms that comprise the S&P 100 index, we only retain observations on CDS contracts with no restructuring (XR) or modified restructuring clause (MR), on senior debt, denominated in US dollars. After applying these initial filters to data on credit default swaps, and merging with OptionMetrics, we are left with a sample of 106 unique firms, covering a total of 9,457 firm-month observations during the sample period 2004 to 2014. Table 1 lists the firms included in our sample.

We average daily mid-quotes of the CDS contracts within a calendar month to obtain a time series of monthly average credit default swap rates for each firm. Over the entire sample period, the average (median) firm's 1-year and 5-year CDS rates are 44.1 basis points (21.9 bp) and 85.4 basis points (54.5 bp) with considerable variation both across firms and within firms over time.

To obtain estimates of the *level* of implied volatility for each firm, we interpolate implied volatilities of one-month out-of-the money call and put options with strike prices closest to the current stock price. We measure option *skew* as the difference between the implied volatility of a put option that is one standard deviation out of the money (using the estimate of IV level) and the implied volatility of the at-the-money option (the IV level). We then average the daily estimates for each firm to obtain a monthly time series of firm-level implied volatility level and skew. Over the entire sample period, the average firm's estimates are 0.27 (level) and 0.042 (skew).

Equity market data are from CRSP and we obtain quarterly data on corporate policies from Compustat. Debt is measured as current liabilities (DLCQ) plus long-term debt (DLTTQ). Using CRSP data, market equity is the product of share price (PRC) and number of shares outstanding (SHROUT). Leverage is defined as debt divided by debt plus market equity. The market-to-book ratio is the ratio of debt plus market equity to total assets (ATQ). Over the entire period, the average (median) firm in our sample has market leverage of, on average, about 25.6% (17.6%). Monthly equity log returns for firms in our sample average 0.46% with a standard deviation of 7.61%.

Table 2 summarizes moments of monthly averages of firm fundamentals, equity returns, option characteristics and CDS rates.

3.2 Consumption Dynamics

We use real non-durable and service consumption to estimate the consumption growth dynamics (1). While the majority of the consumption-based asset pricing literature uses either annual or quarterly data, we uses monthly data covering the years 1960 to 2016 because the goal of the model is to match monthly option and CDS moments. For parsimony, we estimate a 4-state Markov switching model with 2 drift and 3 volatility regimes using maximum likelihood. The parameter estimates are reported in Panel A of Table 3.

As the post war period has generated very smooth consumption dynamics, we add a disaster state to the Markov chain. Barro and Ursa (2012) report that consumption disasters occur with a probability of 3.6%, have an average duration of 3.7 years, and cause an average cumulative drop in consumption of 21.6%. For parsimony, we assume that the economy can only switch into a depression from a severe recession with the low drift and high volatility regime. The resulting calibration is summarized in Panels B and C of Table 3.

3.3 Calibration

In Table 4, we summarize the calibrated parameters. Following Bansal and Yaron (2004), we assume that the representative agent a high EIS of 2 and time discount rate β close to one to achieve a low and stable risk-free rate.

To calibrate the conditional moments of earning growth, we use monthly earnings data as reported by Robert Shiller for the S&P 500. Similar to Bansal and Yaron (2004), we assume little correlation between the aggregate Gaussian shocks and set the drift states μ_i by scaling the consumption states μ_c by the factor $\phi_\mu = 2$ to match the monthly correlation between consumption and aggregate earnings of 11.4%, i.e., $\mu_i = \phi_\mu(\mu_c - \mathcal{P}\mu_c) + \mathcal{P}\mu_c$.

We also calibrate debt and equity issuance costs. As Altinkilic and Hansen (2000) report, debt issuance costs are small, especially, for our sample of S&P100 firms. While in the model firms issue debt after a sequence of good shocks, firms raise equity when they are in financial distress and earnings have dropped below interest expenses. Consequently, equity issuance costs have to capture more than just underwriting fees. In particular, firms with net operating losses potentially face the market for lemons phenomenon. In addition, firms do not fully capture net operating loss carry-forwards and carry-backs as shown in Cooper and Knittel (2006).

3.4 Estimation

We structurally estimate the remaining parameters with simulated method of moments (SMM). Specifically, we are interested in the corporate tax rate τ, idiosyncratic risk ζ_i, the amount of systemic risk in earnings $\sigma_i = \phi_\sigma \sigma_c$, risk aversion γ, and the level a and cyclicality b of bankruptcy costs. To estimate these 6 parameters, we compute time-series moments of leverage, returns, CDS, and option moments.

The estimated parameter vector $\theta = (\tau, \zeta_i, \phi_\sigma, \gamma, a, b)$ minimizes a distance metric between key moments from actual data, Ψ^D, and moments from simulated model data, $\Psi^M(\theta)$. Given an arbitrary parameter vector θ, we solve the model numerically, simulate 100 firms for 120,000 months. Since US consumption has not declined by 10% or more, which is the disaster definition of Barro and Ursa (2012), we exclude the disaster state in the simulation. Note that the disaster state still affects prices.

Based on the simulated data panel, we calculate the model moments $\Psi^M(\theta)$ as well as the objective function $[\Psi^D - \Psi^M(\theta)]' W [\Psi^D - \Psi^M(\theta)]$. The parameter estimate $\hat{\theta}$ is found by searching globally over the parameter space. We use the diagonal matrix of the optimal spectral density as weighting matrix and implement the global minimization via a particle swarm algorithm. Computing standard errors for the parameter estimate requires the Jacobian of the moment vector, which we find numerically via a finite difference method.

4 Results

Tables 5 and 6 summarize the SMM estimation. In Table 5, we report parameter estimates for risk aversion γ, aggregate volatility scaling ϕ_σ, corporate tax rate τ, idiosyncratic risk ζ_i, and the level a and cyclicality b of bankruptcy costs for two models. Model 2 targets moments based on leverage, excess returns, 1-year and 5-year CDS rates. For each variable, we first compute the cross-sectional average and then measure the time-series mean and variance. For Model 1, we also add at-the-money implied volatility (IV ATM) and the implied volatility skew (IV skew) as moments. The target moments and data is reported in Table 6. All moments in Tables 6 to 8 are in percent.

In Table 7, we report model implied moments, which were not necessarily targeted but the estimation. Model 2 matches well leverage on average (25.4%) and its standard deviation (2.6%). The model also generates reasonable average credit spreads at the 1-year (26bps) and 5-year horizon (84bps) and credit spread volatilities at the 1-year (43bps) and 5-year horizon (53bps). In contrast, the Model 2 overstates average excess returns (0.77%) and stock return volatility (3.4%).

To match the data, Model 2 requires risk aversion of 9.4 and total asset volatility of 7.5%. In Table 8, we decompose credit risk into LGD and 5-year cumulative default probabilities both under the physical $\mathbb{P}$ and risk-neutral measure $\mathbb{Q}$. The estimated bankruptcy costs parameters are $a = -5.9$ and $b = 6.3$, implying average bankruptcy costs of 29.6% with a standard deviation of 25.2%. These estimates are close to the ones reported in Glover (2006) but he estimates constant bankruptcy costs. Similar to Chen (2010), our estimates imply strongly countercyclical bankruptcy costs.

A shortcoming of the model is the high average LGD rate (97.8%). The reason is that it too cheap for equity holders to raise equity and keep the firm alive, even when earnings drop below coupon payments. Eventually, they declare default, when the present value of dividends turns negative. But their optimal default threshold is very low such that LGD rates are large on average. Larger equity issuance costs would alleviate this problem.

A solution to the credit spread puzzle requires that firms have low leverage (25.4%) and low physical default probabilities (0.75%), which our model satisfies. At the same time, risk-neutral cumulative 5-year default probability are large at about 3.7%. This effect arises because preferences make the low growth rate regimes more likely under the risk-neutral measure. Since the risk-neutral dynamics are key for pricing, credit spreads are large. Figure 6 illustrates this effect.

In Model 1, we also target option pricing moments, in particular, mean and variance of at-the-money implied volatility and the implied volatility skew. While Model 2 highly overstates at-the-money implied volatility (37.4%) and the implied volatility skew (5.5%), Model 1 generates reasonable at-the-money implied volatility (32.1%) and implied volatility skew (4.3%).

The model can match option moments because of the depression state, which makes out-of-the-money put options a valuable hedge against severe economic downturns. Our model mechanism avoids the critique of Backus, Chernov, and Martin (2011), who show that consumption-based asset pricing models based on variable rare disasters as in Barro (2006) severely overstate the option skew. The reason is that we model depressions as a state of persistently lower growth rates and higher volatility as opposed to a one-shot drop in consumption as in the previous literature. The later mechanism has a far more severe effect on the value of short-dated options. The top two panels of Figure 5 shows option characteristics in the model as a function of the firm's state. The horizontal axis shows the firm's leverage ratio (which is a one-to-one function of its interest-coverage-ratio), whereas the two lines represent two of the model's five macroeconomic states. The model replicates the fact that, for any economic regime, both the level and skew of the implied volatility surface are increasing in leverage. For a fixed leverage ratio, the level of implied volatilities is higher in recessions, whereas the skew is roughly unchanged. It is important to note, however, that leverage ratios increase in recessions, so that the observed level and skew are both higher in recessions than in expansions, as in the data.

Model 1 does a better job in matching both credit and option markets, while Model 1 performs better on credit risk moments only. What are the economics? Since Model 2 overstates at-the-money IV and IV skew, Model 1 has less idiosyncratic risk (7.1%) than Model 2 (5.1%) and also less total risk 6.7% relative to 7.5%. The reduction in total risk implies a better fit for option market moments. At the same time, the aggregate volatility scaling parameter increases from 6.7 for Model 2 to 12.7 for Model 1, implying that a larger fraction of total risk is systematic.

For Model 1 to match credit spreads, the model requires not only more systematic risk in earnings but also higher bankruptcy costs. In Model 1, the estimated bankruptcy costs parameters are $a = -4.8$ and $b = 0.8$, implying average bankruptcy costs of 58.8% with a standard deviation of 0.5%. Thus, adding option market moments to the estimation of bankruptcy costs is important because option IV and skew is informative about the composition of risk.

5 Conclusion

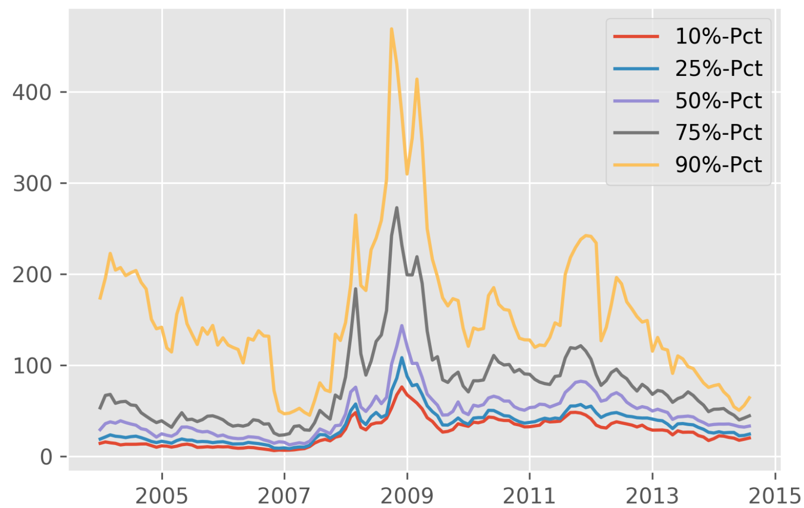

Figure 1: This figures shows five percentiles of the cross-sectional CDS distribution.

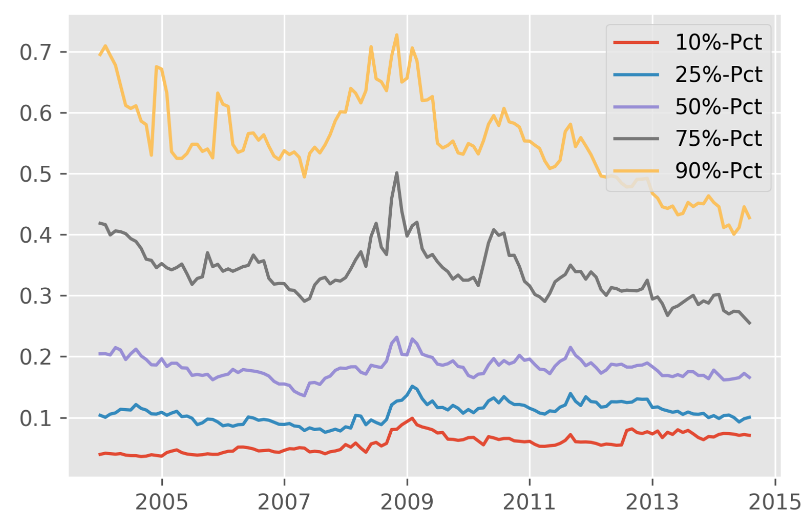

Figure 2: This figures shows five percentiles of the cross-sectional market leverage distribution.

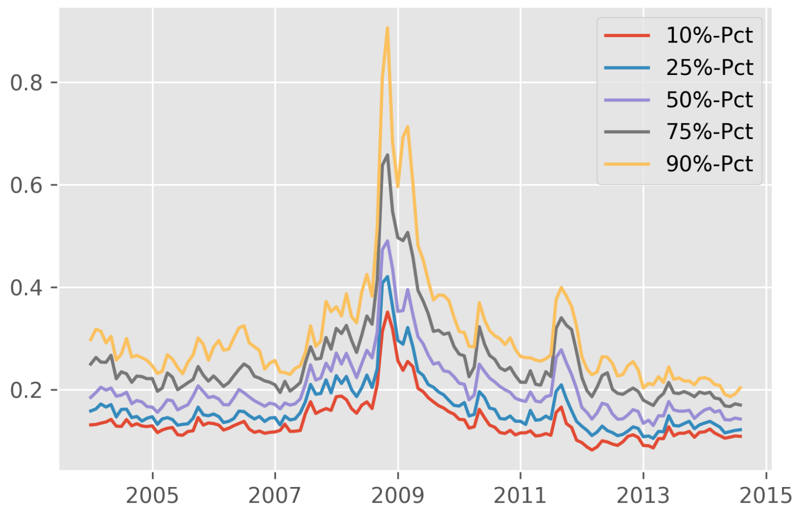

Figure 3: This figures shows five percentiles of the cross-sectional implied volatility distribution.

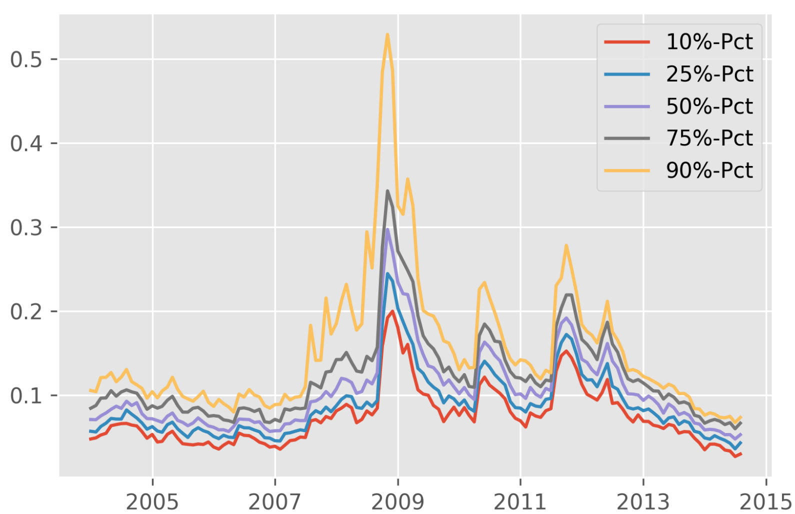

Figure 4: This figures shows five percentiles of the cross-sectional implied volatility skew distribution.

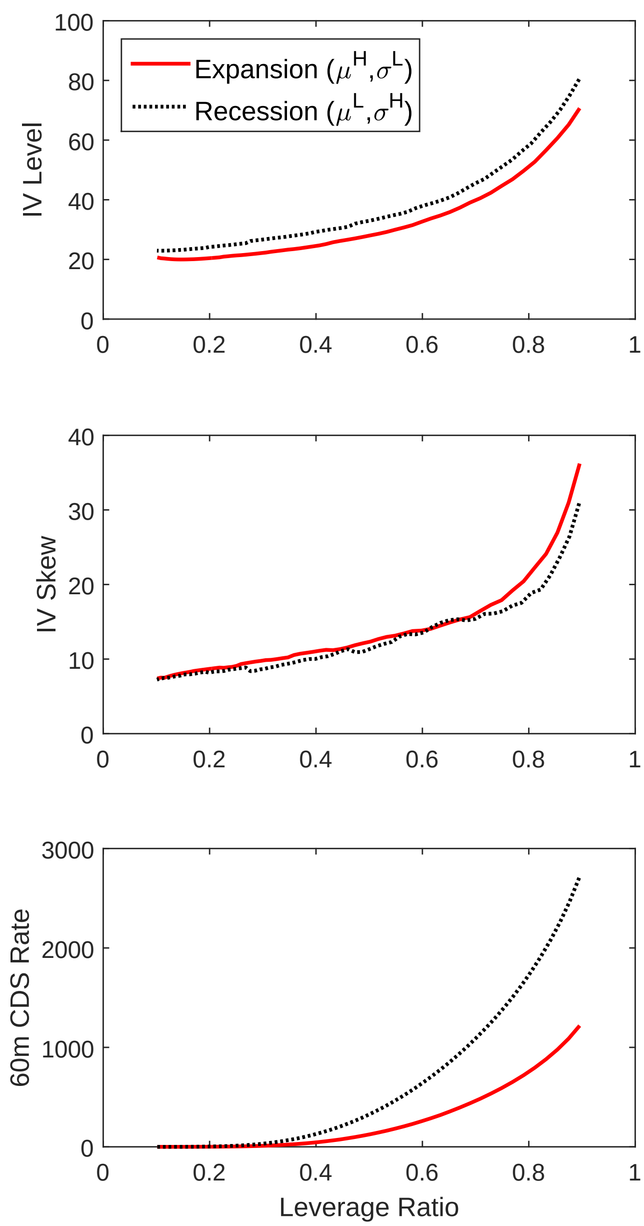

Figure 5: This figures shows derivative prices as a function of firms' leverage ratio for the benchmark calibration. The monthly CDS rate is reported in bps p.a.

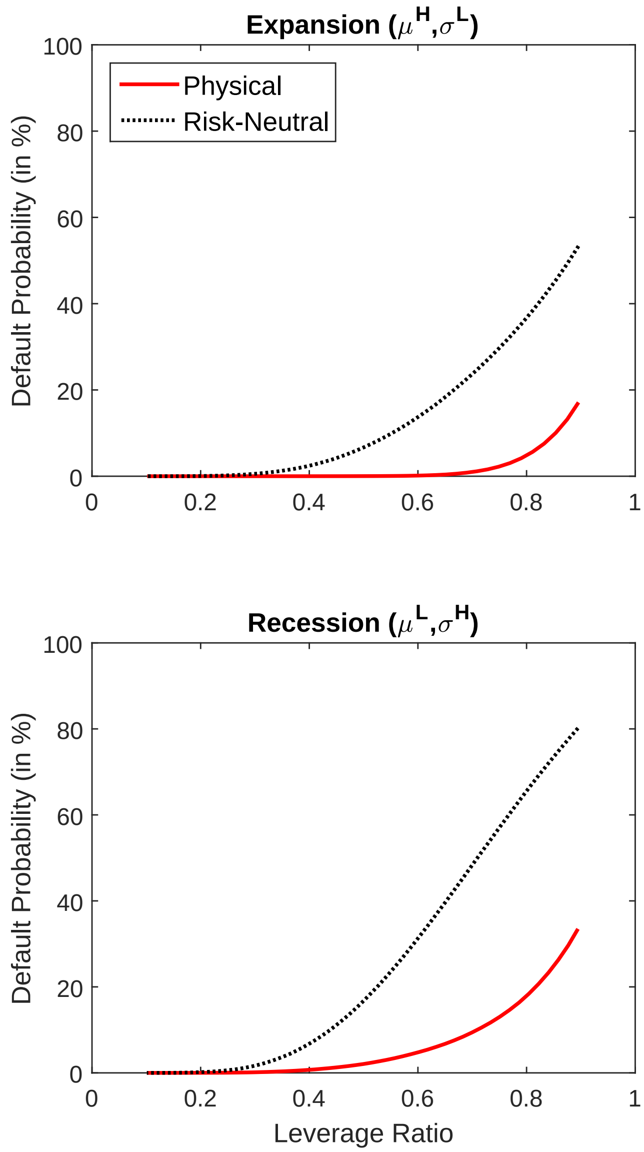

Figure 6: This figures shows default probabilities under the physical and risk-neutral measures as a function of firms' leverage ratios.

Table 1: Sample Firms

#	Company Name	First Date	Last Date
1	3M Company	01/2004	08/2014
2	AES Corp.	01/2004	11/2008
3	AT&T Corp.	01/2004	11/2005
4	AT&T Inc.	01/2004	08/2014
5	Abbott Laboratories	08/2005	08/2014
6	Alcoa Inc.	01/2004	02/2012
7	Allstate Corp	01/2004	08/2014
8	Altria Group Inc	01/2004	08/2014
9	American Electric Power Co Inc	01/2004	02/2014
10	American Express Company	01/2004	08/2014
11	American International Group, Inc.	01/2004	08/2014
12	Amgen Inc	01/2004	08/2014
13	Anadarko Petroleum Corp.	03/2012	08/2014
14	Anheuser-Busch Companies Inc.	01/2004	11/2008
15	Apache Corp	03/2011	08/2014
16	Apple Inc.	05/2013	08/2014
17	Avon Products	01/2004	02/2012
18	Baker Hughes Inc.	01/2004	05/2013
19	Baxter International Inc.	01/2004	08/2014
20	Black & Decker Corporation	01/2004	02/2007
21	Boeing Co.	01/2004	08/2014
22	Bristol-Myers Squibb Co	01/2004	08/2014
23	Burlington Northern Santa Fe Corp.	01/2004	02/2010
24	CVS Caremark Corporation	03/2007	08/2014
25	Campbell Soup Company	01/2004	02/2011
26	Capital One Financial Corp.	12/2006	08/2014
27	Caterpillar Inc.	08/2005	08/2014
28	Chevron Corporation	10/2005	08/2014
29	Cigna Corp	01/2004	11/2008
30	Cisco Systems Inc.	01/2004	08/2014
31	Citigroup Inc	01/2004	08/2014
32	Clear Channel Communications Inc	01/2004	07/2008
33	Coca-Cola Co	01/2004	08/2014
34	Colgate-Palmolive Company	01/2004	08/2014
35	Computer Sciences Corp.	01/2004	06/2007
36	ConocoPhillips	12/2006	08/2014
37	Costco Wholesale Corp.	01/2009	08/2014
38	Dell Inc	07/2004	12/2012
39	Devon Energy Corporation	12/2008	08/2014
40	Dow Chemical Company	01/2004	08/2014
41	Du Pont E.I. de Nemours & Co	01/2004	08/2014
42	EL Paso Corp	01/2004	11/2008
43	Eli Lilly and Company	03/2012	08/2014
44	Emerson Electric Co.	03/2011	08/2014
45	Entergy Corp	01/2004	02/2012
46	Exelon Corporation	01/2004	08/2014
47	Exxon Mobil Corporation	01/2004	08/2014
48	FedEx Corporation	01/2004	08/2014
49	Ford Motor Co	01/2004	08/2014
50	General Dynamics Corp	01/2004	08/2014
51	General Electric Company	08/2013	08/2014
52	Gillette Company	01/2004	09/2005
53	Goldman Sachs Group Inc	01/2004	08/2014
54	HCA Inc	01/2004	11/2006
55	Halliburton Co	01/2004	08/2014

(continued on next page)

#	Company Name	First Date	Last Date
56	Hartford Financial Services Group	01/2004	11/2008
57	Heinz (HJ) Co.	01/2004	05/2013
58	Hewlett-Packard Co	01/2004	08/2014
59	Home Depot Inc.	01/2004	08/2014
60	Honeywell International Inc	01/2004	08/2014
61	Intel Corporation	11/2008	08/2014
62	International Business Machines Corp.	01/2004	08/2014
63	International Paper Co.	01/2004	11/2008
64	Johnson & Johnson	01/2004	08/2014
65	Lehman Brothers Holdings Inc.	01/2004	09/2008
66	Lockheed Martin Corporation	12/2008	08/2014
67	Lowe‘s Companies, Inc.	12/2008	08/2014
68	Lucent Technologies Inc.	01/2004	11/2006
69	McDonald’s Corporation	01/2004	08/2014
70	Medtronic Inc.	01/2004	08/2014
71	Merrill Lynch & Co Inc	01/2004	12/2008
72	Metlife, Inc.	06/2009	08/2014
73	Microsoft Corp.	05/2008	08/2014
74	Monsanto Company	03/2009	08/2014
75	Morgan Stanley	01/2004	08/2014
76	Nextel Communications Inc	01/2004	08/2005
77	Nike Inc.	03/2009	08/2014
78	Norfolk Southern Corp.	01/2004	08/2014
79	Occidental Petroleum Corp.	09/2008	08/2014
80	Oracle Corporation	01/2004	08/2014
81	Pepsico Inc.	01/2004	08/2014
82	Pfizer Inc	01/2004	08/2014
83	Philip Morris International Inc.	05/2008	08/2014
84	Procter & Gamble Co	01/2004	08/2014
85	RadioShack Corp	01/2004	10/2006
86	Schering-Plough Corporation	12/2008	11/2009
87	Schlumberger Ltd	01/2004	08/2014
88	Southern Company	04/2008	08/2014
89	Target Corporation	07/2005	08/2014
90	Texas Instruments Inc.	04/2008	08/2014
91	Time Warner Inc.	01/2004	08/2014
92	Toys R US Inc.	01/2004	07/2005
93	U.S. Bancorp	07/2008	08/2014
94	Union Pacific Corp.	03/2011	08/2014
95	Unisys Corporation	01/2004	09/2006
96	United Parcel Service Inc.	11/2005	08/2014
97	United Technologies Corp.	01/2004	08/2014
98	UnitedHealth Group Inc	01/2008	08/2014
99	Verizon Communications Inc	08/2004	08/2014
100	Wal-Mart Stores Inc.	01/2004	08/2014
101	Walgreen Company	08/2014	08/2014
102	Wells Fargo & Company	01/2004	08/2014
103	Weyerhaeuser Co	01/2004	02/2012
104	Williams Cos. Inc.	01/2004	11/2013
105	Wyeth	11/2008	10/2009
106	Xerox Corp.	01/2004	02/2012

Table 2: Data Summary Statistics

The table shows moments of monthly averages of firms in our sample for the period from January 2004 to August 2014.

			Quantiles				
Variable	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Leverage	0.2546	0.0216	0.2154	0.2417	0.2502	0.2635	0.3332
Log Returns (percent)	0.5174	4.6746	-23.6156	-1.3549	1.3602	2.9430	11.5785
CDS rate 1-year (bp)	44.1237	59.2457	7.0986	14.5443	25.9309	44.9193	315.2057
CDS rate 5-year (bp)	79.5972	50.2398	29.1947	51.2816	69.0547	86.7866	299.4803
IV	0.2692	0.1051	0.1619	0.2100	0.2360	0.2863	0.7825
Skew	0.0432	0.0215	0.0206	0.0304	0.0374	0.0462	0.1522

Table 3: Consumption Dynamics

Based on monthly real non-durable and service consumption for the years 1960 to 2016, we estimate a 4-state Markov chain using maximum likelihood.

Panel A: ML Estimation

$\mu_{c,h}$	$\mu_{c,l}$	$\sigma_{c,h}$	$\sigma_{c,l}$
0.2935	0.0932	0.4211	0.1855
(0.0119)	(0.0241)	(0.0153)	(0.0087)
p_μ^{hh}	p_μ^{ll}	p_σ^{hh}	p_σ^{ll}
0.9971	0.9776	0.9939	0.9941
(0.0202)	(0.0031)	(0.0058)	(0.0045)

Panel B: Consumption and Earnings States

$\mu_{c,h}$	$\mu_{c,l}$	$\mu_{c,d}$
0.2935	0.0932	-0.6180
$\sigma_{c,l}$	$\sigma_{c,h}$	$\sigma_{c,d}$
0.1855	0.4211	0.8422
μ_h	μ_l	μ_d
0.3485	-0.0521	-1.4745

Panel C: Transition Matrix

(μ_h, σ_l)	(μ_l, σ_l)	(μ_h, σ_h)	(μ_l, σ_h)	(μ_d, σ_d)
0.9912	0.0029	0.0059	0.0000	0
0.0223	0.9718	0.0001	0.0058	0
0.0061	0.0000	0.9910	0.0029	0
0.0001	0.0060	0.0223	0.9567	0.0149
0	0	0	0.0225	0.9775

Table 4: Calibrated Parameters

EIS	ψ	2
Time discount rate	β	0.996
Consumption-earnings correlation	ρ	0.1
Drift scaling	ϕ_μ	2
Bankruptcy costs maximum	$\bar{\omega}$	0.6
Debt issuance costs	ψ_d	0.005
Equity issuance costs	ψ_e	0.1

Table 5: SMM Parameter Estimates

Parameter		Model 1	Model 2
Risk aversion	γ	8.9739	9.3898
Aggregate volatility scaling	ϕ_σ	12.6524	6.7387
Tax rate	τ	0.2210	0.2191
Idiosyncratic volatility	ζ_i	0.0509	0.0712
Bankruptcy cost level	a	-4.8367	-5.9145
Bankruptcy cost cyclicality	b	0.8276	6.3269
J-test	J	0.1082	0.0388

Table 6: SMM Moments

	Data	Model 1	Model 2
Average leverage	25.4622	25.4473	25.3791
Average excess returns	0.4657	0.6527	0.7775
Average 1-year CDS	0.4412	0.1478	0.2589
Average 5-year CDS	0.7960	0.7247	0.8397
Average IV ATM	26.9235	32.0791	37.4105
Average IV skew	4.3228	4.2607	5.4838
Variance of leverage	0.0463	0.0534	0.0668
Variance of returns	0.2170	0.0778	0.1158
Variance of 1-year CDS	0.0035	0.001	0.0019
Variance of 5-year CDS	0.0025	0.0027	0.0028
Variance of IV ATM	1.0968	0.2734	0.0772
Variance of IV skew	0.0459	0.0216	0.0265

Table 7: Model Implied Moments

	Data	Model 1	Model 2
Average leverage	25.4622	25.4473	25.3791
Average excess returns	0.4657	0.6527	0.7775
Average 1-year CDS	0.4412	0.1478	0.2589
Average 5-year CDS	0.7960	0.7247	0.8397
Average IV ATM	26.9235	32.0791	37.4105
Average IV skew	4.3228	4.2607	5.4838
S.D. of leverage	2.1592	2.3114	2.5836
S.D. of returns	4.6766	2.7890	3.4024
S.D. of 1-year CDS	0.5925	0.3202	0.4325
S.D. of 5-year CDS	0.5024	0.5155	0.5327
S.D. of IV ATM	10.5141	5.2285	2.7790
S.D. of IV skew	2.1510	1.4686	1.6284
Correlation: leverage, 1-year CDS	81.0254	32.0273	42.4492
Correlation: leverage, 5-year CDS	80.6382	68.5033	80.7723
Correlation: 5-year CDS, IV ATM	92.2990	70.9865	80.7106
Correlation: 5-year CDS, IV skew	91.0976	31.4147	33.7302

Table 8: CDS Decomposition

	Model 1	Model 2
Average bankruptcy costs	58.8261	29.5787
S.D. of bankruptcy costs	0.4860	25.2268
Average LGD under $\mathbb{P}$	95.9246	97.7624
Average LGD under $\mathbb{Q}$	95.9678	97.7872
S.D. of LGD under $\mathbb{P}$	0.9184	0.3273
S.D. of LGD under $\mathbb{Q}$	0.9577	0.3047
Average 5-year def. probability under $\mathbb{P}$	0.5362	0.7534
Average 5-year def. probability under $\mathbb{Q}$	3.6029	3.7320
S.D. of 5-year def. probability under $\mathbb{P}$	0.6280	0.6229
S.D. of 5-year def. probability under $\mathbb{Q}$	2.1647	1.8173