Review of Finance *forthcoming* (January 2019) 1–60

Specification Analysis of Structural Credit Risk Models*

Jing-Zhi Huang[1], Zhan Shi[2] and Hao Zhou[3]
[1]*Smeal College of Business, Pennsylvania State University;* [2]*PBC School of Finance, Tsinghua University;* [3]*PBC School of Finance, Tsinghua University*

Abstract. Empirical studies of structural credit risk models so far are often based on calibration, rolling estimation, or regressions. This paper proposes a GMM-based method that allows us to both consistently estimate the model parameters and test whether all the restrictions of the model are satisfied. We conduct a specification analysis of five representative structural models based on the proposed GMM procedure, using information from both equity volatility and term structures of single-name credit default swap (CDS) spreads. Our test results strongly reject the Merton (1974) model and two diffusion-based models with a constant default boundary. The other two models, one with jumps and one with stationary leverage ratios, do improve the overall fit of CDS spreads and equity volatility. However, all five models have difficulty capturing the dynamic behavior of both equity volatility and CDS spreads, especially for investment-grade names. On the other hand, these models have a much better ability to explain the sensitivity of CDS spreads to equity returns.

JEL Classification: G12, G13, C51, C52

*The authors would like to thank Amit Goyal (the editor), an anonymous referee, Jean Helwege, George Tauchen, Marliese Uhrig-Homburg; seminar participants at Arizona, Central University of Finance and Economics, Cheung Kong Graduate School of Business, China Europe International Business School, Lehigh, MIT, Shanghai University of Finance and Economics; and conference participants and especially discussants at the 2006 Econometric Society North American Winter Meeting in Boston (discussant: Viral Acharya), the 2006 Derivatives and Risk Management Conference at FDIC, the 2007 Federal Reserve Board Conference on Credit Risk and Credit Derivatives, Moody's 4th Annual Credit Risk Conference in Copenhagen (Rangarajan Sundaram), the 2007 Gutmann Center Symposium on Credit Risk and the Management of Fixed-Income Portfolios in Vienna (Thomas Dangl), the 2007 China International Conference in Finance (Yi Zhou), the 2008 Mitsui Symposium at Michigan (Ren-Raw Chen), the 2008 Singapore International Conference on Finance (Jan Ericsson), the 2008 Northern Finance Association Meeting in Manitoba (Pascal Francois), and the 2009 American Finance Association Meeting in San Francisco (Ilya Strebulaev) for helpful comments and suggestions. Huang acknowledges a Smeal Summer Research Grant for partial support.

1. Introduction

A widely used approach to credit risk modeling is the so-called structural method, originated from Black and Scholes (1973) and Merton (1974). A growing literature has empirically examined the implications of structural models for various financial variables, such as credit spreads (Eom, Helwege, and Huang, 2004), real default probabilities (Leland, 2004), both spreads and default rates (Huang and Huang, 2012), hedge ratios (Schaefer and Strebulaev, 2008), corporate bond return volatility (Bao and Pan, 2013), and prices of different seniority levels (Bao and Hou, 2017). The main empirical methods used in this literature include calibration, rolling estimation, and regressions. Although these methods are intuitive, easy to implement, and widely used, it is known that, from a statistical point of view, they have some limitations.

In this paper, we propose an alternative approach to testing structural credit risk models. More specifically, we construct a specification test based on certain model-implied variables, such as credit spreads and equity volatility. By assuming that both equity and credit markets are efficient and that the underlying structural model is correct, we obtain moment restrictions on model parameters (e.g., asset volatility and default boundary). We then use generalized method of moments (GMM) of Hansen (1982) to conduct parameter estimation as well as specification analysis of the structural model. Three aspects of this GMM-based specification test are worth noting. First, the test provides consistent econometric estimation of the model parameters. Second, the test allows us to conduct a precise inference on whether the model is rejected or not in the data. Third, the test is based on the joint behavior of time-series asset dynamics and cross-sectional pricing errors for structural models.

For illustration, we apply the proposed approach to five affine, representative structural models of default that incorporate various economic considerations. For each of the five models, we construct its moment conditions using equity volatility and term structures of single-name credit default swap (CDS) spreads. We then test whether all the restrictions of the model are satisfied using the GMM, based on the model implied CDS spreads and equity volatility. By minimizing the effect of measurement error from using firm characteristics, this test attributes the test results mostly to the specification error. Lastly, we examine the ability of the model to explain equity volatility, the CDS term structure, default rates, sensitivity of CDS spreads to equity returns, etc.

For the purpose of this study, using CDS data has at least two advantages over using corporate bond data. One is that CDS spread curves are readily available. The other is that in general the CDS market is more liquid than the corporate bond market. We include equity return volatility in moment conditions mainly because few empirical studies have examined the implications of structural models for this second moment variable.[1] In other words, while equity volatility is usually used as an input in the empirical literature on structural models, this study treats equity volatility as an output of the models. Additionally, we use the so-called "model-free" realized equity volatility in our empirical analysis. As it is estimated using intraday high-frequency equity returns and involves no overlapping observations, realized volatility is more accurate than volatility estimates based on daily or monthly returns. Moreover, the use of the latter estimates implies that structural models are implicitly assumed to be able to fit perfectly the time series of equity volatility involving overlapping observations. Lastly, focusing on realized equity volatility is consistent with the evidence that volatility dynamics has a strong potential in better explaining credit spreads (e.g., Zhang, Zhou, and Zhu, 2009).

For reasons of tractability and comparison, we focus on the Merton (1974) model and its four extensions with an exogenous default boundary in this study. The four barrier-type models include the Black and Cox (1976) model with a flat default boundary, the Longstaff and Schwartz (1995) model with stochastic interest rates, the Collin-Dufresne and Goldstein (2001) model with a stationary leverage, and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002) and Kou (2002).[2]

[1] There is ample empirical evidence that individual equity volatility is time-varying and stochastic (see, e.g., the survey articles by Bollerslev, Chou, and Kroner, 1992; Bollerslev, Engle, and Nelson, 1994). This stylized fact should be taken into account in examining structural models that consider equity to be a contingent claim on the underlying firm asset value.

[2] Kou (2002) develops the first DEJD-based equity option pricing model. Concurrently, Ramezani and Zeng (2007) use the DEJD to model individual stock returns. Huang and Huang (2002, 2012) provide the first application of the DEJD model in credit risk. Other examples using the DEJD-based structural model include Cremers, Driessen, and Maenhout (2008); Bao (2009); Chen and Kou (2009).

We test each of the five models using a sample of 93 industrial companies in the U.S. that have a balanced panel of monthly realized equity volatility and CDS term structure over the period January 2002–December 2004. As the main purpose of our empirical analysis is to illustrate the proposed specification test of structural models, the choice of the sample period is not essential to the analysis. Nonetheless, this post dot-com bubble (and also post the Enron collapse) period includes many major corporate defaults and "actions." On the other hand, relatively "quiet" compared to the recent financial crisis, this sample period is less subject to illiquidity concern documented for the corporate bond market during the financial crisis (Dick-Nielsen, Feldhütter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012).

Our GMM-based specification tests strongly reject the Merton, Black and Cox, and Longstaff and Schwartz models. The DEJD model is found to significantly outperforms these three models. The Collin-Dufresne and Goldstein model is the best performing one among the five models: the model is not rejected by the GMM test for more than half of the 93 companies in our sample. Nonetheless, the fact that both the DEJD and CDG models are still rejected by a substantial number of firms in the sample indicates that something is missing in these models.

The pricing error results from the five models provide similar evidence. On the one hand, jumps and dynamic leverage help improve the model fit for investment-grade (IG) and high-yield names, respectively. On the other hand, the five models all substantially underestimate both equity volatility and CDS spreads for IG names during 2002 when credit risk is relatively high. In other words, these models have difficulty in capturing the dynamic behavior of both equity volatility and CDS spreads, especially for IG names—even though equity volatility in structural models is time-varying.

Interestingly, all five models, especially the Merton model, fare better in describing the sensitivity of CDS spreads to equity returns, in terms of the number of firms where the model-implied sensitivity is not rejected in our sample. Moreover, evidence from the actual hedging performance indicates that the Merton model surprisingly outperforms the other four models.

To summarize, this study contributes to the credit risk literature by proposing and implementing a GMM-based specification test of structural models. Importantly, this approach, among other things, makes use of the advantages of GMM—its convenience and generality (see, e.g., Jagannathan, Skoulakis, and Wang, 2002). Our empirical findings (albeit based on a short sample) shed light on how to improve the existing structural models. Specifically, incorporating stochastic asset volatility and jumps into the Merton (1974) model may improve the ability of the model to predict not only CDS spreads and equity volatility but also hedge ratios of CDS spreads.[3]

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 briefly outlines the class of structural models examined in our empirical analysis. Section 4 presents our econometric method of parameter estimation and specification tests. Section 5 describes the data used in our analysis, and Section 6 reports and discusses our empirical findings. Finally, Section 7 concludes.

2. Related Literature

Empirical studies of structural models go back to Jones, Mason, and Rosenfeld (1984), who implement a rolling estimation approach. Examples of following this approach include Eom, Helwege, and Huang (2004), Hull, Nelken, and White (2004), Arora, Bohn, and Zhu (2005), and Bao (2009). Huang and Huang (2002, 2012) propose a calibration approach with representative firms, which is also used in Chen, Collin-Dufresne, and Goldstein (2008), Schaefer and Strebulaev (2008), Du, Elkamhi, and Ericsson (2018), McQuade (2018), and Shi (2019). Regression based studies include Collin-Dufresne, Goldstein, and Martin (2001) and Zhang, Zhou, and Zhu (2009). Ericsson and Reneby (2005) and Predescu (2005) combine a rolling estimation procedure with the MLE approach proposed in Duan (1994).

[3] Du, Elkamhi, and Ericsson (2018) incorporate stochastic volatility into the Merton (1976) jump-diffusion model and find that the resultant SVJ model for the unlevered asset value can jointly capture CDS spreads and option-implied volatilities; McQuade (2018) shows that combining stochastic volatility with endogenous default sheds light on many asset pricing anomalies, including the value premium, financial distress, and momentum puzzles. Both studies illustrate that a reasonable calibration for the variance risk premium allows their stochastic volatility models to match historical corporate yield spreads for medium and longer maturities, offering a potential resolution for the credit spread puzzle (à la Huang and Huang, 2012). Other recent studies of the puzzle include Bai, Goldstein, and Yang (2018); Feldhütter and Schaefer (2018).

Among studies of structural models based on CDS data, Hull, Nelken, and White (2004) implement the Merton (1974) model using a calibration approach. Predescu (2005) examines the Merton model as well as a Black and Cox (1976) type barrier model. Chen, Fabozzi, Pan, and Sverdlove (2006) investigate the Merton, Black-Cox, and Longstaff-Schwartz models. Bao (2009) and Bai and Wu (2016) focus on the cross-section of spreads implied by structural models. Examples of studies that link CDS premiums with variables from structural credit risk models using a regression analysis include Ericsson, Jacobs, and Oviedo (2009); Zhang, Zhou, and Zhu (2009).

This paper differs from the aforementioned studies in that it proposes and conducts a GMM-based specification test of structural models. Additionally, equity volatility is treated as an output variable in the proposed test.

Our paper also fits in the literature on the implications of structural models for second moment variables (such as equity return volatility) as well as on their impact on credit risk. For instance, Campbell and Taksler (2003) find that idiosyncratic equity volatility can explain a significant part of corporate bond yield spreads cross-sectionally. Huang and Huang (2012) conjecture that a structural credit risk model with stochastic asset volatility may help solve the credit spread puzzle. Huang (2005) considers an affine class of structural models with both stochastic asset volatility and Lévy jumps. Based on regression analysis, Zhang, Zhou, and Zhu (2009) provide empirical evidence that a stochastic asset volatility model may improve the model performance. Perrakis and Zhong (2015) extend the Leland and Toft (1996) model to allow for constant elasticity of variance. Kelly, Manzo, and Palhares (2016) provide more recent evidence of stochastic asset volatility. See also Du, Elkamhi, and Ericsson (2018) and McQuade (2018). In a closely related study, Bao and Pan (2013) focus on corporate bond return volatility and document that the volatility implied from the Merton (1974) model with stochastic interest rate underestimates substantially the observed corporate bond return volatility.

The literature on hedge ratios implied by structural models goes back to Schaefer and Strebulaev (2008), who find that on average, the Merton model-implied sensitivity of a firm's corporate bond returns to its equity returns is not statistically different from the in-sample empirically estimated hedge ratios. Bao and Hou (2017) investigate how a corporate bond's position in its issuer's maturity structure affects its sensitivity to the issuer's equity return. They show that both the direction and the magnitude of this de facto seniority effect are consistent with what are implied from an extended Merton model. Huang and Shi (2016) examine the actual hedging performance of model-implied sensitivities of corporate bond returns and spreads, which is equivalent to testing the out-of-sample explanatory power of the hedging portfolio. Additionally, they document that on average, the Merton model also captures the in-sample sensitivity of spreads to the equity return. On the other hand, focusing on pairs of stock returns and CDS spread changes with the same underlying over a short interval (e.g., five days), Kapadia and Pu (2012) find that about 41% of stock returns are associated with CDS spread changes in the same direction, as opposed to the prediction of the Merton model. This discrepancy is shown to reflect an imperfect equity-credit market integration at short horizons. Huang, Rossi, and Wang (2015) find similar results based on pairs of stock and corporate bond returns and also provide evidence that equity market sentiment helps improve the equity-credit market integration especially after the financial crisis.

In this study we examine not only hedge ratios but also hedging performance of structural models. In addition, we go beyond the Merton model.[4]

As mentioned before, we use CDS data instead of corporate bond data in the empirical analysis, partly to avoid the liquidity problem in the latter market. For recent evidence on corporate bond illiquidity, see Bao, Pan, and Wang (2011); Chen, Lesmond, and Wei (2007); Das and Hanouna (2009); Han and Zhou (2016); Helwege, Huang, and Wang (2014); Longstaff, Mithal, and Neis (2005); Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008); Schestag, Schuster, and Uhrig-Homburg (2016); Bongaerts, de Jong, and Driessen (2017), among others. In addition, using term structures of CDS spreads facilitates the implementation of the proposed GMM-based test—it is known that data on term structures of corporate bond spreads are not easily available for individual firms.

Lastly, note that there is a large theoretical literature on structural credit risk modeling (see, e.g., Huang and Huang, 2012; Sundaresan, 2013, and references therein), although for tractability and comparison we consider only five structural models in our empirical analysis. For example, the class of endogenous-default models, not considered in this paper,

[4] To be more precise, the Merton model implemented in this study is the "extended Merton model" tested in Eom, Helwege, and Huang (2004). A similar model is also studied in Bao and Pan (2013).

includes those without strategic default, such as Geske (1977) and Leland and Toft (1996), and strategic default models, such as Anderson and Sundaresan (1996), Mella-Barral and Perraudin (1997), Acharya and Carpenter (2002), and Acharya, Huang, Subrahmanyam, and Sundaram (2006, 2019). Strategic default models of perpetual bonds are considered in Huang and Huang (2012). Endogenous default models with finite maturity of Geske (1977) and Leland and Toft (1996) are examined in Eom, Helwege, and Huang (2004). Another example not covered in this paper is the Duffie and Lando (2001) model with incomplete accounting information. Additionally, François and Morellec (2004) examine the impact of the US bankruptcy procedure on risky debt prices. He and Xiong (2012) and He and Milbradt (2014) consider both rollover risk and corporate bond illiquidity.

3. Affine Structural Credit Risk Models

This section first reviews the five structural credit risk models to be tested in our specification analysis, and then apply the models to the CDS pricing. Lastly, we discuss the model implications for equity volatility and sensitivities of CDS spreads to equity return.

3.1 Models

For completeness, below we briefly review the five structural models to be tested in our empirical study. Although these models differ in certain economic assumptions, they can be embedded in the same underlying structure that includes specifications of the underlying firm's asset process, the default boundary, the recovery rate, etc.

Let V be the firm's asset process, K the default boundary, and r the default-free interest rate process. Assume that, under a risk-neutral measure $\mathbb{Q}$,

$$\frac{dV_t}{V_{t-}} = (r_t - \delta)dt + \sigma_v dW_t^Q + d\left[\sum_{i=1}^{N_t^Q}\left(Z_i^Q - 1\right)\right] - \lambda^Q \xi^Q dt, \tag{1}$$

$$d\ln K_t = \kappa_\ell \left[-\nu - \phi(r_t - \theta_r) - \ln(K_t/V_t)\right] dt, \tag{2}$$

$$dr_t = (\alpha - \beta\, r_t)\, dt + \sigma_r\, dZ_t^Q, \tag{3}$$

where δ, σ_v, κ_ℓ, ν, ϕ, α, β, σ_r, and $\theta_r = \alpha/\beta$ are constants, and W^Q and Z^Q are both one-dimensional standard Brownian motion under the risk-neutral measure and are assumed to have a constant correlation coefficient of ρ. In Eq. (1), the process N^Q is a Poisson process with a constant intensity $\lambda^Q > 0$, the Z_i^Q's are i.i.d. random variables, and $Y^Q \equiv \ln(Z_1^Q)$ has a double-exponential distribution with a density given by

$$f_{Y^Q}(y) = p_u^Q \eta_u^Q e^{-\eta_u^Q y} \mathbf{1}_{\{y \geq 0\}} + p_d^Q \eta_d^Q e^{\eta_d^Q y} \mathbf{1}_{\{y < 0\}}. \quad (4)$$

In Eq. (4), parameters $\eta_u^Q, \eta_d^Q > 0$ and $p_u^Q, p_d^Q \geq 0$ are all constants, with $p_u^Q + p_d^Q = 1$. The mean percentage jump size ξ^Q is given by

$$\xi^Q = \mathbf{E}^Q \left[e^{Y^Q} - 1 \right] = \frac{p_u^Q \eta_u^Q}{\eta_u^Q - 1} + \frac{p_d^Q \eta_d^Q}{\eta_d^Q + 1} - 1. \quad (5)$$

All five models are special cases of the general specification in Eqs. (1)–(5). For instance, if the jump intensity is zero, then the asset process is a geometric Brownian motion. This specification is used in the four diffusion models, namely, the models of Merton (1974), Black and Cox (1976, BC hereafter), Longstaff and Schwartz (1995, LS hereafter), and Collin-Dufresne and Goldstein (2001, CDG hereafter).

Regarding the specification of the default boundary K, it is a point at the bond maturity in the Merton model. If κ_ℓ is set to be zero, then the default boundary is flat (a continuous barrier), an assumption made in the BC, LS, and the double-exponential jump diffusion (DEJD) models.

If both β and σ_r in Eq. (3) are zero, then the interest rate is constant. This leads to the three one-factor models: the Merton, BC, and DEJD models.

If both β and σ_r in Eq. (3) are greater than zero, then we have the two-factor models, LS and CDG, where the dynamics of the risk-free rate follow the Vasicek model specified in Eq. (3). Additionally, the CDG model assumes that $\kappa_\ell > 0$ and that the default boundary follows the mean-reverting specification in Eq. (2).

Lastly, we obtain the DEJD model if the jump intensity is strictly positive, the risk-free rate is constant, and the default boundary is flat.

We assume a constant recovery rate for comparison with other studies and also because the CDS database that we use includes the recovery rate estimates.

3.2 Valuation of Single-Name CDS Contracts

Under each of the five structural models, it is straightforward to calculate the CDS spread. Let $Q(0, T)$ denote the survival probability over $(0, T]$ under the T-forward measure. Then the CDS spread of a T-year CDS contract is given by

$$\mathrm{cds}(0,T) = \frac{(1-R)\,X_t}{\sum_{i=1}^{4T} B(0,T_i)Q(0,T_i)/4}\,, \tag{6}$$

where R is the recovery and $B(0,\cdot)$ the default-free discount function. X_t denotes the price of the Arrow-Debreu default claim, or equivalently, the present value of one dollar paid upon default

$$X_t = E^Q\left[e^{-\int_0^{\tau} r(u)du}\, I_{\{\tau<T\}}\right], \tag{7}$$

where τ is the default time, r the interest rate process, $I_{\{\cdot\}}$ the indicator function, and $E^Q[\cdot]$ the expectation under the risk-neutral measure. To simplify the computation, we follow the literature to make the standard assumption that the settlement of the contract occurs on the next payment day. It then follows from Eq. (6) that

$$\mathrm{cds}(0,T) = \frac{(1-R)\,\sum_{i=1}^{4T} B(0,T_i)[Q(0,T_{i-1})-Q(0,T_i)]}{\sum_{i=1}^{4T} B(0,T_i)Q(0,T_i)/4}. \tag{8}$$

As a result, the implementation of a structural model amounts to the calculation of the survival probability $Q(0,\cdot)$. In the Merton (1974) and the Black and Cox (1976) models, $Q(0,\cdot)$ has closed form solutions. The survival probability in the DEJD model and the two-factor models do not have a known closed-form solution but can be calculated using a numerical method (see, e.g., Huang and Huang, 2012, for details).

In addition to CDS spreads, other model-implied credit market variables include CDS spread changes, CDS volatilities, and corporate bond return volatilities, etc. However, corporate bond volatilities have a sizable illiquidity component and CDS volatilities might also be a bit high compared to fundamentals (Bao and Pan, 2013; Bao, Chen, Hou, and Lu, 2015). Therefore, given the purpose of this study, we do not consider these second moment variables in credit markets in our empirical analysis.

3.3 Equity Market Variables

In this subsection we focus on more liquid equity market variables, which have received relatively little attention in the empirical literature on structural models.

Consider equity return volatility first. As pointed out by Merton (1974), the delta function relating the equity volatility and asset volatility is also model-dependent

$$\sigma_E(t) = \sigma_v \frac{V_t}{E_t}\frac{\partial E_t}{\partial V_t}, \tag{9}$$

where the equity volatility $\sigma_E(t)$ is generally time-varying while the asset volatility σ_v may be constant. For the DEJD process, the equity volatility of the continuous diffusion component satisfies Eq. (9).

Next, we consider the comovement between CDS and equity, in order to better understand the relative pricing of these two markets as well as the hedge of common exposures across markets. Following Schaefer and Strebulaev (2008), we can express the sensitivity of CDS spread to the equity of the firm in terms of partial derivatives with respect to the firm value

$$\Delta_{E,t}^{cds} = \frac{\partial \text{cds}(t,T)}{\partial E_t/E_t} = \frac{\partial \text{cds}(t,T)/\partial V_t}{\partial E_t/\partial V_t} E_t. \tag{10}$$

As illustrated in Section 4.1, both $\partial \text{cds}(t,T)/\partial V_t$ and $\partial E_t/\partial V_t$ are functions of $\partial Q(t,\cdot)/\partial V_t$, the sensitivity of risk-neutral survival probabilities to asset value. As such, once $Q(t,\cdot)$ is known, $\Delta_{E,t}^{cds}$ can be calculated.

Unlike its counterpart for corporate bonds, the hedge ratio for a CDS contract is not the same as its sensitivity to equity. Instead, the latter hedge ratio is defined as the dollar change in the value of the CDS contract for each percentage change in the equity value

$$h_{E,t}^{cds} = \frac{\partial V_t^{cds}}{\partial E_t/E_t} = \frac{\partial \text{cds}(t,T)}{\partial E_t} E_t Z_t, \tag{11}$$

where V_t^{cds} denotes the time-t value of a CDS contract with a notional of \$10 million, and $Z_t = \sum_{i=1}^{4T} B(t,T_i)Q(t,T_i) \times 2.5$ million is defined as the change in the mark to market value (in million) for each unit of change in the quoted spread.[5]

4. A Specification Test of Structural Models

In this section we propose a specification test of structural models under the GMM framework of Hansen (1982). We first review the framework albeit using moment conditions

[5] We use the ISDA CDS Standard model to mark a given CDS contract to market. Documentation of the model as well as the source code for the model is available at www.cdsmodel.com.

pertinent to structure models. We then discuss finite sample properties of GMM. Lastly, we focus on the implementation of the proposed specification test.

4.1 GMM Estimation of Structural Credit Risk Models

As mentioned before, the fundamental pricing relationship implied by a structural model has implications for credit spreads, equity volatility, default probabilities, leverage, corporate bond returns, corporate bond return volatility, hedge ratios, etc. To evaluate the model, we first estimate the model parameters that may include asset volatility, default barrier, asset jump intensity, or dynamic leverage coefficients, etc. Let θ denote the vector of the model parameters to be estimated and $\widehat{\theta}$ the estimated vector. We then take $\widehat{\theta}$ as given and examine the pricing performance of the (estimated) model. Below we describe how to implement this idea using GMM, following largely Cochrane (2009).

As noted before, we focus on model-implied CDS spreads and equity volatility in the empirical analysis. Let $\text{cds}(t, t+T_m)$ and $\sigma_E(t)$ be the time-t CDS spread with maturity $t+T_m$ and equity volatility under a given structural model, specified in Eqs. (8) and (9), respectively. Let $\widetilde{\text{cds}}(t, t+T_m)$ and $\widetilde{\sigma_E}(t)$ be the time-t observed counterparts of $\text{cds}(t, t+T_m)$ and $\sigma_E(t)$. Consider the following vector of pricing errors (so-called moment conditions):

$$f(\theta, t) = \begin{bmatrix} \widetilde{\text{cds}}(t, t+T_1) - \text{cds}(t, t+T_1) \\ \cdots\cdots\cdots\cdots\cdots\cdots \\ \widetilde{\text{cds}}(t, t+T_M) - \text{cds}(t, t+T_M) \\ \widetilde{\sigma_E}(t) - \sigma_E(t) \end{bmatrix}, \tag{12}$$

where M denotes the number of CDS contracts with different maturities included in $f(\theta, t)$. Under the null hypothesis that the model is correctly specified, we have

$$E[f(\theta, t)] = 0. \tag{13}$$

To test the above hypothesis, we construct a time series of $f(\theta, t)$ over the sample period and consider its time-series mean in the following:

$$g(\theta, T) \equiv \frac{1}{T} \sum_{t}^{T} f(\theta, t). \tag{14}$$

In other words, $g(\theta, T)$ represents the sample mean of the moment conditions. If $M = \dim(\theta) - 1$ (i.e., the number of moment conditions is the same as the number of parameters to be estimated), then we can pick θ such that $g(\theta, T) = 0$. In general, however, $M > \dim(\theta) - 1$ as in our case; that is, there are more moment conditions than parameters. In this case, we can pick θ such that linear combinations of the moment conditions are zero. This is a challenging task, however, especially given that both CDS spreads and equity volatility are allowed to be observed with measurement errors in this analysis. As such, we choose θ to minimize a quadratic function of the pricing errors. Doing so leads to the so-called GMM estimator:

$$\widehat{\theta} = \arg\min g(\theta, T)' W(T) g(\theta, T), \tag{15}$$

where $W(T)$, a weighting matrix, denotes the asymptotic covariance matrix of $g(\theta, T)$ (Hansen, 1982). With mild regularity conditions, $\widehat{\theta}$ is $\sqrt{T}$-consistent and asymptotically normally distributed, under the null hypothesis.

Furthermore, we implement the iterative GMM. That is, we begin with $W(T) = I$, the identity matrix, and estimate θ. Next, we use a heteroscedasticity robust estimator for the variance-covariance matrix $W(T)$ that allows for autocorrelation in the errors (Newey and West, 1987), and obtain a new $\widehat{\theta}$. We repeat this procedure until it converges.

Given $\widehat{\theta}$ that minimizes the quadratic form specified in Eq. (15), we can then examine how well the candidate model fits. If the pricing errors are "large" under the appropriately defined GMM metric, the candidate model specification will be rejected. Formally, we conduct the following test:

$$J_T = T \min_{\theta} g(\theta, T)' W(T) g(\theta, T) \sim \chi^2(N^{oi}), \tag{16}$$

where $N^{oi} = M + 1 - \dim(\theta)$, the degree of freedom of the χ^2 distribution, equals the number of overidentifying moment conditions. As a result, the GMM J_T test allows for an omnibus test of the overidentifying restrictions.

4.2 Finite Sample Properties of GMM

The J_T-test specified in Eq. (16) is an asymptotic test. Several studies have examined finite sample properties of GMM estimators applied to asset pricing models, although the literature has focused mainly on consumption-based models and linear factor models in the equity market (see, e.g., Hall, 2005, and references therein). For instance, Tauchen (1986) considers the Hansen and Singleton (1982) consumption based asset pricing model and examines the behavior of the two-step GMM estimator using one asset in the estimation. He finds that the bias of the estimator tends to increase as the degree of overidentification (N^{oi}) increases but the empirical sizes of the J_T test tend to be close to the asymptotic value. Kocherlakota (1990) extends the analysis of Tauchen (1986) to multiple assets and his findings suggest that the iterated GMM estimator considerably improves the finite sample behavior of GMM. Using predictive regression models for stock returns, Ferson and Foerster (1994) find that while sizes of the two-step GMM based J_T statistics are often too large with finite samples, the iterated GMM approach has superior finite sample properties. Hansen, Heaton, and Yaron (1996) consider a consumption-based asset pricing model where the representative agent's utility function allows for time non-separability. They find that when the number of the overidentifying restrictions is high (five), the asymptotic theory is far from the finite sample property. Lettau and Ludvigson (2001) argue that the one-stage GMM is more appropriate than the two-stage GMM with an estimated weighting matrix in the application pursued in their study—where the time series sample is small relative to the cross-sectional sample size.

In our specification analysis, we test a given candidate model firm by firm. Based on the insights from the aforementioned studies, in order to mitigate the potential small sample problems in our tests, we need to keep the degree of overidentification minimal. As discussed in Section 4.3, for a given firm, the number of parameters to be estimated using the GMM ranges from one for the Merton model to four for the CDG model. As such, we use four CDS contracts and realized equity volatility (i.e., five moment conditions) with 36 monthly observations in each GMM test. That is, the degree of overidentification ranges from one in CDG to four in Merton in our tests. As a robustness check, we also test the Merton model using one CDS contract and realized equity volatility such that the degree of overidentification is one. The number of time series observations relative to the number of moment conditions is reasonably large, given that the latter is no more than five in our tests. Additionally, we implement the iterative GMM. Taken together, the findings of the aforementioned studies based on the equity market suggest that small sample problems are not a major concern in our GMM tests.

4.3 Implementation

In this subsection we discuss the implementation of the proposed GMM specification test. First, to make the estimation tractable, we separately estimate the interest rate process from firm-specific model parameters for the two models with stochastic interest rates (the LS and CDG models). This is a reasonable strategy, since the interest rate parameters are common inputs in these models and those firm-specific parameters do not affect the interest rate process.

We use the 3-month LIBOR as a proxy for the short rate (r_t) in the estimation. We estimate the interest rate volatility using $\widehat{\sigma}_r = \text{VAR}(r_t)$. Given that the one-factor Vasicek (1977) model is a crude approximation to the observed term structure dynamics, we opt to estimate the risk-neutral drift parameters, α and β, month-by-month as follows:

$$\{\hat{\alpha}_t, \hat{\beta}_t\} = \arg\min \sum_{T=T_1}^{T_6} \left[y_{t,t+T}^{\text{data}} - y_{t,t+T}(\alpha, \beta) \right]^2 ,$$

where the term structure of observed interest swap rates used in the above nonlinear least square estimation is $y_{t,t+T}^{\text{data}}$ with $T = 1, 2, 3, 5, 7$, and 10 years—matching CDS maturities included in our sample (see Section 5.1). The cross-sectional pricing errors of the Vasicek model range from 12 to 112 basis points (bps) during the full sample period. The sample mean of monthly estimates $(\hat{\beta}_t, \hat{\sigma}_{r,t})$, which are obtained by rolling-window estimations, are 0.3820 and 0.0156, respectively; while $\hat{\beta}_t$ is larger than those reported in previously studies based on much longer samples (Schaefer and Strebulaev, 2008; Bao and Pan, 2013), the magnitude of $\hat{\sigma}_{r,t}$ is consistent with their estimates.

Next, we focus on those firm-specific model parameters. For ease of reference, let θ denote the vector of these parameters in the discussion that follows—namely, θ does not include $(\alpha, \beta, \sigma_r)$. For a given structural model, we estimate its parameter vector θ in two steps.

In step one, fixing an initial θ, we calculate the month-t model-implied CDS spreads, $cds(t, \cdot) = \{cds(t, t + T_j)\}_{j=1}^{J}$, and the model-implied equity volatility, $\sigma_E(t)$, using Eqs. (8) and (9), respectively.[6] Given the model-implied $cds(t, \cdot)$ and $\sigma_E(t)$, we then compute the

[6] In connection with Eq. (9), we implicitly include the empirically observed (quasi-market) leverage ratio as one moment condition by imposing the following constraint during the estimation: at the end of each month, for every firm in our sample, we adjust the coupon

month-t vector $f(\theta, t)$ of pricing errors defined in Eq. (12). Repeating this for every month, we obtain a time series of vector $f(\theta, t)$ as well as its sample mean, $g(\theta, T)$ in Eq. (14), over the full sample period.

In step two, we solve the optimization problem specified in Eq. (15), where the weighting matrix $W(T)$ is estimated iteratively—and in each iteration we use the Newey-West auto-correlation robust estimator of the covariance matrix with three lags.

In the two-step procedure outlined above, one key component is the choice of the initial θ. In the case of the Merton model, $\theta = (\sigma_v)$. The initial $\sigma_v = \sigma_E L_q$, where the quasi market leverage ratio $L_q = F/(F + E)$, F denotes the total debt (book value), and E the market equity value. In the case of the Black-Cox model, $\theta = (\sigma_v, K)$. The initial σ_v is the estimate of σ_v obtained using the Merton model. We set the initial K to 1.2 if $\bar{L} < 0.2$; 1 if $0.2 < \bar{L} \leq 0.4$; 0.8 if $0.4 < \bar{L} \leq 0.6$; 0.6 if $0.6 < \bar{L} \leq 0.8$; and 0.4 if $\bar{L} > 0.8$, where $\bar{L}$ is the firm's mean leverage ratio over the full sample period. Such choice of the initial (σ_v, K) is also followed in the estimation of the LS, CDG, and DEJD models.

In the case of the two-factor LS model, we need to estimate (σ_v, K, ρ), where the initial correlation coefficient ρ used is the correlation between equity returns and the interest rate. Estimates of ρ obtained in the literature, however, are usually zero or slightly negative (see, e.g., Eom, Helwege, and Huang, 2004; Schaefer and Strebulaev, 2008; Bao and Pan, 2013). Therefore we restrict ρ to be zero in the estimation of the LS model. As a result, $\theta = (\sigma_v, K)$ in this case.

The other two-factor model, the CDG model, involves five parameters: $(\sigma_v, \rho, \kappa_\ell, \nu, \phi)$. Results from an untabulated analysis indicate that coefficients ρ and ϕ seem difficult to be simultaneously identifiable and that ρ is not bounded between -1 and +1. As a result, we impose the restriction that $\rho = 0$. Doing so also makes it easier to see the incremental impact of the stationary leverage ratio relative to the LS model. It follows that the vector of parameters to be estimated using GMM is $\theta = (\sigma_v, \kappa_\ell, \nu, \phi)$. The initial values of κ_ℓ, ν, ϕ are chosen to be the same as the values used in CDG.

In the case of the DEJD model, the model parameters include $(\sigma_v, K, \lambda^Q, p_u^Q, \eta_u^Q, \eta_d^Q)$. The latter three parameters, (p_u^Q, η_u^Q, η_d^Q), however, enter the solution function multiplicatively with λ^Q as in $\lambda^Q \xi^Q$ and, as a result, are very difficult to identify in our GMM

rate of its debt such that it is valued at par and, as a result, that the market value of the firm is equal to (market equity + book debt).

estimator. To overcome this technical difficulty in the GMM estimation of the DEJD model, we let $\theta = (\sigma_v, K, \lambda^Q)$, and restrict the domain of $(p_u^Q,\ \eta_u^Q,\ \eta_d^Q)$ to the following particular values: $p_u^Q \in \{0.25, 0.5, 0.75\}$, $\eta_u^Q \in \{3, 5\}$, and $\eta_d^Q \in \{3, 5\}$, where the inputs of (η_u^Q, η_d^Q) are motivated by the calibration exercise of Huang and Huang (2002). In our estimation, for each firm, we choose the particular set of jump parameters with the smallest J-statistic as the "best" jump model estimate. The initial λ^Q is set to 0.1.

5. Data Description

Data used in our study include single-name credit default swap (CDS) spreads, data on intraday equity returns (used to estimate realize equity volatility), firm balance sheet information, and risk-free interest rates. In this section we describe each of these four data sets in detail, and then present summary statistics on CDS spreads and firm characteristics.

5.1 Credit Default Swap Spreads

We use CDS data from Markit, a comprehensive data source that assembles a network of industry-leading partners who contribute information across several thousand credits on a daily basis. Based on the contributed quotes, Markit creates the daily composite quote for each CDS contract, which must pass the stale data test, flat curve test, and outlying data test. Together with the pricing information, the Markit data set also reports average recovery rates used by data contributors in pricing each CDS contract. In addition, an average of Moody's and S&P ratings is also included.

We begin with collecting all CDS quotes written on US entities (sovereign entities excluded) and denominated in US dollars. Following previous empirical studies on structural models (e.g., Eom, Helwege, and Huang, 2004), we exclude financial and utility sectors from the sample. In addition, we focus on the senior unsecured CDS contracts and eliminate the subordinated class of CDS contracts, because of their small relevance in the database and unappealing implication in credit risk pricing. Furthermore, we limit our sample to CDS contracts with modified restructuring (MR) clauses, as they are the most popularly traded in the US market.

For the purpose of GMM estimation, we restrict the sample to those CDS names with at least 36 consecutive monthly observed spreads to be included in the sample. Another filter used is that CDS data need to match equity price from CRSP, equity volatility from NYSE Trade and Quote (TAQ) and accounting variables from Compustat. Application of these filters results in a final sample of 93 entities.

The Markit data set has single name CDS spreads available for maturities of 0.5, 1, 2, 3, 5, 7, 10, 15, 20, and 30 years. Due to the liquidity concern and missing values, we focus on CDS spreads with maturities of 1 through 10 years. For each entity, we create the monthly CDS spread by selecting the latest composite quote in each month, and, similarly, the monthly recovery rates linked to CDS spreads. Our final sample includes 93 single names with monthly CDS spreads for maturities of 1, 2, 3, 5, 7, and 10 years over the period January 2002–December 2004.

5.2 Equity Volatility from High Frequency Data

By the theory of quadratic variation, it is possible to construct increasingly accurate measure for the model-free realized volatility or average volatility, during a fixed time interval (say, a day or a month), by summing increasingly finer sampled squared high-frequency returns (Andersen, Bollerslev, Diebold, and Labys, 2001; Barndorff-Nielsen and Shephard, 2002; Meddahi, 2002). In testing structural models, asset return volatility is often backed out from (observed) equity return volatility (e.g., Jones, Mason, and Rosenfeld, 1984; Eom, Helwege, and Huang, 2004), therefore a more accurate measure of equity volatility from high-frequency data is critical in correctly estimating the asset return volatility—a driving force behind the firm default risk.

Let $s_t \equiv \log S_t$ denote the day t logarithmic price of the firm equity, and the intraday returns are defined as follows:

$$r^s_{t,i} \equiv s_{t,i\cdot\Delta} - s_{t,(i-1)\cdot\Delta}, \tag{17}$$

where $r^s_{t,i}$ refers to the i^{th} within-day return on day t and Δ is the sampling frequency and chosen to be 5-minute. The realized equity volatility (squared) for period t is given as

$$\widetilde{\sigma_E}(t)^2 \equiv \sum_{i=1}^{1/\Delta} (r^s_{t,i})^2 \tag{18}$$

which converges to the integrated or average variance during period t. For a jump-diffusion model, the continuous component of equity volatility (squared) can be estimated with the so-called "bi-power variation"

$$\widetilde{\sigma_E}(t)^2 \equiv \frac{\pi}{2} \frac{1/\Delta}{1/\Delta - 1} \sum_{i=2}^{1/\Delta} |r^s_{t,i-1}||r^s_{t,i}| \ . \tag{19}$$

As shown by Barndorff-Nielsen and Shephard (2004), such an estimator of realized equity volatility is robust to the presence of rare and large jumps. The data are provided by the NYSE TAQ data base, which includes intraday (tick-by-tick) transaction data for all securities listed on NYSE, AMEX, and NASDAQ. The monthly realized variance is the sum of daily realized variances, constructed from the squares of log intraday 5-minute returns. Then, monthly realized volatility is just the square-root of the annualized monthly realized variance.

5.3 Capital Structure and Asset Payout

Assets and liabilities are key variables in evaluating structural models of credit risk. The accounting information is obtained from Compustat on a quarterly basis and assigned to each month with the quarter. We calculate the firm asset as the sum of total liability plus market equity, where the market equity is obtained from the monthly CRSP data on shares outstanding and equity prices. Leverage ratio is estimated by the ratio of total liability to the firm asset. The asset payout ratio is estimated by the weighted average of the interest expense and dividend payout. Both ratios are reported as annualized percentages.

5.4 Risk-Free Interest Rates

To proxy the risk-free interest rates used as the benchmark in the calculation of CDS spreads, we use the 3-month LIBOR and the interest rate swaps with maturities of 1, 2, 3, 5, 7, and 10 years. These data are available from the Federal Reserve H.15 Release.

5.5 Summary Statistics

Table 1 provides summary statistics on firm characteristics and CDS spreads across either rating categories (panel A) or sectors (panel B). As can be seen from panel A1, our sample is concentrated in A-rated (25) and BBB firms (45), which account for 75 percent of the full sample, reflecting the fact that contracts on investment-grade names dominate the CDS market. In terms of the average over both the time-series and cross-section in our sample, the 5-year CDS spread is 144 bps with a standard deviation of 3.18 percent, equity volatility 38.40 percent (annualized), the leverage ratio 48.34 percent, asset payout ratio 2.14 percent, and the quoted recovery rate 40.30 percent. As expected, the CDS spread, equity volatility, and the leverage ratio all increase as rating deteriorates. On the other hand, the recovery rate largely decreases as rating deteriorates but has low variations.

Figure 1 plots both the term structure (from 1 year to 10 years) and time evolution of the average CDS spreads over the full sample period January 2002–December 2004. Clearly, the average spreads show large variations and have a peak around late 2002.

Figure 2 plots both the 5-year CDS spreads (top panel) and equity volatility (bottom panel) by three different rating groups (AAA–A, BBB, and BB–CCC) over the full sample period. A casual inspection of the figure indicates that CDS spreads and equity volatilities appear to move together sometime during market turmoils but are only loosely related during quiet periods. The 5-year CDS spreads clearly have a peak in late 2002 across all three rating groups, although the high-yield group has another spike in late 2004. On the other hand, equity volatility is much higher in 2002 than the later part of the sample period and, in particular, has two huge spikes in 2002. There is clear evidence that equity volatility and credit spreads are intimately related (Campbell and Taksler, 2003), and the linkage appears to be nonlinear in nature (Zhang, Zhou, and Zhu, 2009). In the next section we examine whether structural credit risk models can capture the dynamics of the CDS spreads and equity volatility in our sample.

6. Empirical Results

In this section we present the results from our empirical analysis. We first report the results from the GMM specification test proposed in Section 4. We then discuss the GMM estimates of the model parameters and the pricing performance of the five structural models considered. Next, we provide some diagnostics on various model specifications based on the pricing errors. Lastly, we focus on the model implications for hedge ratios and default probabilities.

6.1 GMM Specification Test

Our GMM specification test is based on the model implied pricing relationship for CDS spread and equity volatility. Table 2 reports the test results, in particular, the number of firms where each of the five candidate models is *not* rejected, for the whole sample as well as subsamples by either credit ratings (panel A) or sectors (panel B). Note from the table that at the conservative 10% significance level, the number of firms (out of 93) where the given model is not rejected is 0, 1, 2, 13, and 52 for the Merton, BC, LS, DEJD, and CDG models, respectively. At the 1% significance level, none of the five models have a rejection rate of 100% and the number of firms with the model not being rejected increases to 5, 6, 12, 42, and 72 for the Merton, BC, LS, DEJD, and CDG models, respectively. Judged by these results on the number of firms where each of the five models is not rejected, the ranking of these models is as follows

$$\text{Merton} \approx \text{Black-Cox} < \text{LS} \ll \text{DEJD} < \text{CDG}$$

Notably, the two more recent models—the DEJD and CDG models—outperform the other three models. This finding implies that both jumps and time varying leverage improve noticeably the model performance.[7] Although it is known that the Merton model underperforms the richer models, the new evidence presented here against the model is based on a consistent econometric test that takes into account the dynamic behavior of both CDS spread curves and equity volatility.

Granted, GMM omnibus tests may be biased toward over-rejection of the true model specification. As a robustness check, we repeat the GMM test of the Merton model using only one CDS contract (the 5-year one) and realized equity volatility. The results from this test with the degree of overidentification being one show that the number of firms with the Merton model not being rejected is still zero at the 10% significance level but

[7] Eom, Helwege, and Huang (2004) find that the CDG model marginally improves the fitting of bond spreads over the LS model. One possible reason why we find that the improvement over LS here is significant is the use of CDS spreads in our tests. Another possible reason is that the risk-neutral leverage parameters are estimated directly here rather than indirectly through their counterparts under $\mathbb{P}$, as alluded in Eom et al. (2004).

increases to 20 at the 1% significance level (untabulated). These results indicate that when the degree of overidentification decreases from four to one, the GMM test indeed rejects the Merton model considerably less at the 1% significance level. Nonetheless, the number of firms not rejecting the model (20) is still way below that for either the DEJD model (42) or the CDG model (72).

As such, our findings provide new evidence on the relative performance of the five candidate models. Furthermore, given that even the highest-ranking model, the CDG model, is rejected by 21 out of 93 firms at the 1% significance level, the results in Table 2 also indicate that the five representative models considered here are still missing something.

6.2 Parameter Estimation

Although the GMM method provides a consistent test of the models, it does not necessarily force the parameter estimates to be plausible in the estimation. Thus, it is important to examine the model parameters and model implications for other moments or variables using the estimated models. We focus on estimates of model parameters (θ) in this subsection and investigate the latter aspect of the analysis in Sections 6.5 and 6.6.

Recall from Section 4.3 that vector θ does not include those predetermined parameter inputs in the case of the two-factor models and the DEJD model. Table 3 reports parameter estimates $\hat{\theta}$ and their standard errors across either credit ratings or sectors. Panel A shows the results for the asset volatility parameter σ_v, which enters all five models. This parameter is significant at all conventional statistical levels. The level of the estimates is reasonable in all models: the mean (median) asset volatility ranges from 0.154 (0.135) for the Merton model to 0.199 (0.170) for the CDG model. The standard deviation of $\widehat{\sigma}_v$ ranges from 0.007 for the Merton model to 0.09 for the LS model.

Panel B of Table 3 reports the estimated default barrier scaled by the total debt, an important parameter in the three models with a flat default boundary. The estimated K/F has a mean (median) of 1.18 (1.06), 1.16 (1.05), and 0.83 (0.75) for the BC, LS, and DEJD models, respectively. This result is intuitive albeit not surprising. To see that, relative to the BC model, the LS model needs a higher K in order to "mitigate" the negative impact of a negative ρ (the correlation between the asset return and the interest rate) on the CDS spread. On the other hand, relative to the same benchmark, the DEJD model requires a lower K given the positive impact of the jump risk on the CDS spread.

We also observe that the median K/F for investment-grade (IG) names is higher than the median for high-yield (HY) names across all three models. In particular, in the LS model while the median for IG names is greater than one, the median for HY names is below one. Similar results obtain when we plot the estimated K/F the observed leverage ratio F/V_t. As can be seen from Figure 3, the slope is significantly negative, indicating that a higher K/F is associated with a lower observed leverage (which is usually associated with a higher credit rating). These results on a negative relationship between the default boundary and the credit rating/observed leverage are also consistent with the evidence documented in Eom, Helwege, and Huang (2004) based on the LS model with corporate bond data.

Columns 3–5 in panel C of Table 3 report the estimates of the risk-neutral jump intensity parameter (λ^Q) in the DEJD model. Note that the full-sample mean and median of $\widehat{\lambda}^Q$ are 0.181 and 0.126, respectively. Across different rating categories, the median $\widehat{\lambda}^Q$ levels for HY names are much higher than those for investment-grade names. For instance, the median is 0.123 for BBB names and 0.209 for BB names. This variation in $\widehat{\lambda}^Q$ across different rating groups partly explains the negative relation between the estimated default boundary and the credit rating discussed earlier (panel B of the table).

The remaining columns in panel C of Table 3 show the estimates of the three leverage parameters in the CDG model, κ_ℓ (columns 6-8), ν (columns 9–11), and ϕ (columns 12–14). Recall that κ_ℓ is the mean-reverting speed of the risk-neutral log leverage ratio $\log(K_t/V_t)$. The full-sample mean and median of $\hat{\kappa_\ell}$ are around 15.16 and 15.35, respectively. In the IG subsample, the median ranges from 15.04 for the single AAA-rated name to 17.72 for the AA-rated names; in the HY subsample, the median is -0.021 for the single CCC-rated name, 1.41 for the BB-rated names, and 5.19 for the B-rated names. These results mean that the median $\widehat{\kappa_\ell}$ is much larger than the calibrated value of 0.18 adopted by CDG or the regression-based estimate obtained in Frank and Goyal (2003), regardless of the rating categories except for the CCC rating group. This finding may be an indication that the CDG model is missing something; it also illustrates the importance of post-estimation examination of the parameter estimates.

Parameter ν is related to θ_ℓ, the long-run mean of the risk-neutral leverage ratio, given that $\theta_\ell = \frac{\delta_t - r_t + \sigma_v^2/2}{\kappa_\ell} + \phi(r_t - \theta) - \nu$. Our choice of estimating a constant ν implies a time-varying but deterministic θ_ℓ. The median of $\widehat{\nu}$ ranges from 0.11 for the lone AAA name to 1.57 for the only CCC-rated name. The full sample mean and median are 0.22 and 0.16, respectively, both of which are closer to the calibration value of 0.60 used in CDG.

Parameter ϕ measures the sensitivity of the firm-specific leverage ratio dynamics to the risk-free interest rate, similar to the risk factor loading in standard asset pricing models. The full sample mean and median are 2.83 and 1.88, respectively. Across different rating groups, the median lies in between 1.18 and 3.15 except for the single CCC-rated name whose $\widehat{\phi}$ is about 37.42. There is substantial variation in $\widehat{\phi}$ within each rating group except for the single AAA- and CCC-rated names. For instance, in the BB-rated group, the 5th- and 95th-percentiles are about -12.19 and 11.76, respectively. The above results suggest that firms have very different leverage ratio dynamics as the macroeconomic risk changes over time. Such a heterogeneity of dynamics leverage ratio seems to be the key for the CDG model to pass the GMM specification test with more than half of the sample.

6.3 Pricing Performance Evaluation

As the evaluation of structural models is usually based on comparing their pricing errors on corporate bonds in the literature, we examine the pricing errors of candidate models (after the parameters are consistently estimated and model specification tests are conducted) in this subsection.

To be more specific, given a candidate model and its estimated model parameters, in each month we calculate the model implied equity volatility and CDS spreads for each maturity including 2 and 7 years. Note that while 2- and 7-year contracts are too sparse to be included in estimation, they are still useful to be included in pricing error evaluation. Then we compute the simple difference, absolute difference, and percentage difference between the model implied and observed ones, for every name in the sample. Next, we calculate the mean of the pooled pricing errors.

Table 4 reports the pricing errors on CDS spreads for the full sample as well as by each rating group and sector. In terms of pricing errors on the spread level (panel A), the overall average pricing error is negative except for the Merton model. This is to say that on average, the Merton model overestimate the CDS spread while the other four models underestimate the spreads.[8] Specifically, the average pricing error is -0.18% for CDG, -0.44% for DEJD, -0.71% for LS, and -0.91% for BC. Thus, the CDG and DEJD model under-fit the spread less than do the BC and LS models.

Note that the overall positive pricing error of the Merton model is mainly driven by the four B-rated names and single CCC-rated name (Delta Air Lines) in the sample. To see that, recall first from Table A1 that these five names all have high leverage and high equity volatility. Delta Air has an equity volatility of 81.9% and a leverage of 93.9%; the average equity volatility and leverage on the four B-rated names are 83.2% and 72.6%, respectively. It is known that the Merton-implied short-term spread on such firms can be very high (Merton, 1974). This result also holds for the five B and CCC names in our sample (see panel C of Figure 4). As a result, the Merton pricing error on these names is large as reported in panel A of Table 4. Next, note from panel A that the average pricing error for IG names is negative, regardless of the structural models considered; that is, on average, all five candidate models underestimate the CDS spread on IG names, consistent with the findings of Bao (2009) using the BC and DEJD models as well as those of Eom, Helwege, and Huang (2004) and Huang and Huang (2012) based on IG bonds.

In terms of absolute pricing performance (panel B), the BC and LS models outperform the Merton model but underperform the DEJD and CDG models in both the full sample and each of the seven credit-rating groups (except for the single CCC-rated name where the BC model slightly outperforms CDG). Furthermore, between the two more recent models, the DEJD model performs relatively better for the IG names while the CDG model does better for the HY names (except for the single CCC-rated name). These results contrast the findings of Eom, Helwege, and Huang (2004) based on corporate bond data that richer model specifications do not improve upon the Merton model in terms of pricing errors.

Results on percentage pricing errors, reported in panel C, indicate that on average, the CDG model overestimates the CDS spread while the other four models underestimate the spread. Among the IG names, the Merton, BS, LS, and DEJD models all underestimate the spread substantially in each of the four rating categories, except that the DEJD model

[8] Predescu (2005) also observes that combining equity price and CDS spreads would make the Merton model overfit the spread.

overestimates the single AAA name's spread. On the other hand, the CDG model overestimates the spread for three IG-rated subgroups. These results indicate that although the newer models (DEJD and CDG) do improve upon the older ones (Merton, BC and LS), the CDG model can raise the spread too much for names in certain rating groups in terms of the percentage pricing errors.

Panel D reports the results on absolute percentage pricing errors. The ranking of the five models is largely the same as before: the DEJD and CDG models outperform the BC and LS models, both of which outperform the Merton model. Nonetheless, the accuracy of all five models is still a problem: the average absolute percentage pricing error ranges from 45.6% for the DEJD model to 114.3% for the Merton model. This finding echos a similar one in the corporate bond market documented in Eom, Helwege, and Huang (2004).

Table 5 presents the results on fitting errors of equity volatility. Broadly speaking, they display similar patterns to those on the CDS spreads (Table 4). For instance, consider panel A. Note that for each model the overall sign of fitting errors on equity volatility is consistent with those on CDS spreads, though the magnitude of volatility fitting errors is generally larger. To some extent, this result is not surprising given that credit spreads increase with the asset volatility in the candidate models. Note also that the Merton fitting error is positive overall mainly because of overfitting in the four B-rated and one CCC-rated bonds. In fact, the model under-fits equity volatility of AA and A names substantially. The other four models also under-fit equity volatility of IG names, except for the single AAA-rated name in the case of the BC, LS and DEJD models and for the AA-rated names in the case of the BC model.

In terms of absolute fitting performance (panel B), on average, the DEJD and CDG models have the lowest errors (11.61% and 11.87%, respectively), while the Merton model has the highest one (26.11%). The BC model slightly underperforms CDG but outperforms LS substantially. Between the two more recent models, on average, the DEJD model underperforms CDG in IG names but outperforms CDG in HY names.

In terms of percentage fitting errors on equity volatility (panel C), the overall sign is consistent with those on CDS spreads for the BC, DEJD and CDG models. This is not the case, however, for the Merton and LS models, which both have an overall positive volatility fitting error. Additionally, note that the magnitude of overall percentage fitting errors on equity volatility is much lower than its counterpart on spreads, because the level of equity volatility is typically higher than the CDS spread.

The ranking of the five models based on the overall absolute percentage fitting error on equity volatility (panel D) is the same as that based on the overall absolute fitting error on equity volatility (panel B) except that the BC and CDG models switch their places. In addition, for each of the seven different rating groups, the DEJD model outperforms the CDG model except for the single AAA-rated name.

To summarize, the results of this section provide evidence that the two more recent models (the DEJD and CDG models) outperform the three older ones (the Merton, BC, and LS models) in fitting CDS spreads as well as equity volatility. Nonetheless, we find that on average, the five structural models all underestimate CDS spreads as well as equity volatility for IG names. In addition, the accuracy of all five models in fitting either the CDS spread or equity volatility is low.

6.4 Further Diagnostics on Model Specifications

In this subsection, we try to gain further insights on model specification errors, by examining the model-implied term structure and time series of CDS spreads, along with the model-implied equity volatility. We also discuss some implications of this analysis for improving the standard structural models.

Figure 4 plots the sample average of the CDS term structure from 1 year to 10 years from the observed data (in solid blue) as well as each of the five candidate models, for three different credit-rating groups, AAA-A (top panel), BBB (middle) and BB-CCC (bottom). A few observations are worth mentioning here: (1) all five models underfit the average term structure except for the Merton model that overfits the short end for the BBB and BB-CCC groups; (2) the best-fitting model, CDG, fits the BBB average term structure almost perfectly and underfits slightly for the AAA-A group; (3) the DEJD model is the second best; (4) the BC model largely captures the shape of the average term structure but underfits its level considerably; (5) the LS model slightly underperforms the BC model in the short maturity for IG names but outperforms the model for HY names; (6) the Merton model underfits the AAA-A curve substantially, especially in the long end but underfits the long end of the BBB and BB-CCC curves less than the BC and LS models do.

Overall, both the stationary leverage and the jump-diffusion models match the shape of the average term structure of CDS spreads well, especially for IG names. The two models, however, still underfit the level of the curve, but the stationary leverage model implied curve is much closer to the observed one than the one implied by the jump-diffusion model.

Figure 5 plots the observed 5-year CDS spread against the five model implied ones. For the HY names (the BB-CCC group), all models seem to capture the time-variations of the 5-year CDS spread reasonably well, although the DEJD and CDG models seem to be the best two. Furthermore, while the DEJD model outperforms the CDG mode in the first third of the sample period, the latter outperforms the former in the last third of the sample period. For the IG names (the AAA-A and BBB groups), most models completely miss the dynamics of the CDS spread, especially for the first third of the sample, when the risk-free rate remains as low as 1%. Interestingly, even the best-fitting CDG model that can get the average level right is not able to describe the evolution of the CDS spread. This finding suggests that a time-varying factor in addition to the interest rate and leverage ratio—like stochastic asset volatility—may be needed in order for a structural model to fully capture the temporal changes in CDS spreads for IG names.

Figure 6 reports the average model-implied and fitted equity volatilities over the full sample period, for three different credit-rating groups, AAA-A (top panel), BBB (middle) and BB-CCC (bottom). Note that for both IG groups, all five models miss completely the volatility spikes during the early sample period. Moreover, every model generates a nearly constant equity volatility while the observed equity volatility varies substantially over time. For the HY group, the model performance is relatively better. In particular, the Merton model captures the volatility spikes to some degree and the LS and DEJD models reasonably fit the second half of the volatility time series. However, these results are mainly driven by the unrealistically high model-implied volatility for the single CCC-rated name. Overall, Figure 6 provides evidence suggesting that without time varying asset volatility, the structural models have difficulty replicating the observed equity volatility dynamics, especially for IG names.

Figure 7 plots the initial spot log leverage ratio $\log(K_t/V_t)$ and the long-run mean of risk-neutral log leverage ratio implied from the CDG model, for three different credit-rating groups, AAA-A (top panel), BBB (middle) and BB-CCC (bottom). It is clear from the figure that these two leverages are fairly close to each other for the HY group (the CCC-BB names). On the other hand, for the BBB names the observed leverage is significantly lower than its risk-neutral counterpart, and the difference between the risk-neutral and observed leverages is even more dramatic for the AAA-A names. This finding mirrors the stylized fact that highly profitable firms may opt to borrow little or no debt (Strebulaev and Yang, 2013; Chen and Zhao, 2006). Such a puzzle may be worth further investigation.

In summary, dynamic leverage ratios and, to a lesser degree, jumps seem to be crucial for a structural model to better match the CDS spread and equity volatility than those models without such two features. However, something else is still missing in the candidate models as they all fail to adequately capture the dynamic behavior of CDS spreads and equity volatility, especially for the IG names. Our findings suggest that incorporating a stochastic asset volatility may improve the performance of the existing structural models.

6.5 Model-Implied Equity Sensitivity of CDS Spreads

The implications of the estimated structural models go beyond CDS spreads and equity volatilities, the variables included as moment conditions and examined in Sections 6.3 and 6.4. In this subsection, we focus on one firm specific variable not included in the moment conditions, the sensitivity of CDS spreads to equity return discussed in Section 3.3.

6.5.1 Regression Tests of Model-implied Sensitivities

We first test the accuracy of model-implied sensitivities in a linear regression setting. Consider the following regression model:

$$\Delta\widetilde{\text{cds}}(t,t+5)_i = \alpha_i + \beta_{1,i}\Delta r_{f,t}^{10y} + \beta_{2,i}\Delta_{E,i,t}^{cds} rx_{i,t}^{E} + u_{it}, \tag{20}$$

where $\Delta\widetilde{\text{cds}}(t,t+5)_i$ denotes the monthly change in the observed 5-year CDS spread for firm i; $r_{f,t}^{10y}$ the month-t ten-year zero yield extracted from swap rates, included to control for changes in the "risk-free" term structure; $rx_{i,t}^{E}$ firm-i's monthly equity return minus the one-month LIBOR; and $\Delta_{E,i,t}^{cds}$ is the model-implied sensitivity of the CDS spread to equity return for firm i as specified in Eq. (10),[9] and is calculated using the parameter

[9] In the implementation of Eq. (10), $\partial\text{cds}(t,t+5)_i/\partial V_{i,t}$ is calculated using Eq. (8), and $\partial E_{i,t}/\partial V_{i,t}$ is set to one minus the delta of a 5-year par bond (see footnote 6), an approximation except for the Merton model. In an untabulated analysis based on the BC model,

vector $\widehat{\theta}$ estimated with the full sample (see Section 6.2)—for example, $\widehat{\theta} = (\widehat{\sigma}_v)$ for the Merton model (Section 4.3). If the model accurately describes the equity sensitivity of CDS spreads, the slope coefficient $\beta_{2,i}$ should be equal to one. On the other hand, if the model consistently underpredicts the sensitivity, then $\beta_{2,i}$ is expected to be significantly greater than one.

As such, we can test the null hypothesis (H1) that $\beta_{2,i} = 1$ on a firm-by-firm basis and report the number of firms for which H1 is not rejected in our sample.[10] In the analysis that follows, we conduct the test based on a modified Eq. (20) with a smoothed $\Delta^{cds}_{E,i,t}$:

$$\Delta\widetilde{\text{cds}}(t, t+5)_i = \alpha_i + \beta_{1,i}\Delta r^{10y}_{f,t} + \beta_{2,i}\overline{\Delta}^{cds}_{E,i,t}\, rx^E_{i,t} + u_{it}, \tag{21}$$

where $\overline{\Delta}^{cds}_{E,i,t}$ denotes the month-t average of model-implied sensitivities across firms in the same rating or industry category as firm i. This is because using a smoothed model-implied hedge ratio can help reduce the noise in the firm-by-firm estimates of model parameters (see, e.g., Schaefer and Strebulaev, 2008).

Table 6 reports the results from regression in Eq. (21) where $\overline{\Delta}^{cds}_{E,i,t}$ used is either by ratings (panel A) or by industries (panel B). Consider panel A first. Note that $\bar{\beta}_{2,i}$, the average of the estimates of $\beta_{2,i}$ over the whole sample, is 0.74 and 0.76 for the BC and LS models, respectively, but $\bar{\beta}_{2,i}$ is around one for the other three models. An inspection of the means of $\widehat{\beta}_{2,i}$ in each rating category finds that the means are below one regardless of the rating categories for both the BC and LS models. This result indicates that these two models consistently overpredict the equity sensitivity of CDS spreads. On the other hand, for the Merton and DEJD models, the average $\widehat{\beta}_{2,i}$ is below or very close to one for IG names but is greater than one for HY names—and, in fact, the pair of the coefficients

we find that including the expected bankruptcy cost in $\partial E_{i,t}/\partial V_{i,t}$ has little impact on the model's performance in fitting both CDS spreads and equity volatility as well as in hedging CDS.

[10] This regression test is in the spirit of Schaefer and Strebulaev (2008), who examine the Merton-implied sensitivity of corporate bond returns to equity. The authors focus on the average of regression coefficients (counterparts of $\beta_{2,i}$ estimates here) across bonds in their sample and test whether the mean slope coefficient is close to one. Notably, they find an imprecise estimate of the mean $\beta_{2,i}$ in their AAA rating category, which consists of 23 bonds. Given that there are only 93 observations of the estimated $\beta_{2,i}$ in our entire sample, there are not enough firms available in certain rating/sector categories for a reliable inference based on the mean of the 93 estimates. This mean estimate is reported in Table 6.

for B and CCC names are (2.90, 3.90) and (2.52, 3.49) for the Merton and DEJD models, respectively. The variation in the average $\beta_{2,i}$ across different rating categories is much less for the CDG model, with the average $\beta_{2,i}$ ranging from 0.73 for AA names to 1.25 for AAA- or B-rated names.

For how many firms out of 93 the null hypothesis H1 is not rejected (for a given model), based on the t-statistics (using the Newey-West standard error estimator)? As indicated in panel A, the answer is 72 (Merton), 12 (BC), 18 (LS), 69 (DEJD), and 76 (CDG), at the 5% significance level. Recall from Table 2 that the number of firms where the model is not rejected by the GMM-based specification test at the 5% significance level is 1 (Merton), 1 (BC), 6 (LS), 20 (DEJD), and 63 (CDG). The implication is that all five models capture the sensitivity of CDS spreads to equity much better than they do the CDS spread level and equity volatility. This is true especially for the Merton model.

Regression R^2, shown in the last row of panel A, is 30.4% for Merton, 26.3% for BC, 28.6% for LS, 30.2% for DEJD, and 18.7% for CDG. Note that the R^2 generated by the CDG model is low, and even lower than its counterpart from the otherwise same regression excluding $\overline{\Delta}_{E,i,t}^{cds}$ (untabulated). Furthermore, the R^2 under CDG is the lowest among the five models. How to reconcile this result with the evidence that the number of firms where H1 is not rejected is the highest under CDG? One explanation is that the t-test conducted at the firm level may fail to reject the null hypothesis even if the point estimate of the slope coefficient substantially deviates from unity, due to the large standard error estimated using the Newey-West adjustment. Therefore, although among the five candidate models the CDG model has the largest number of non-rejected firms, the model does not necessarily make the most accurate prediction of hedge ratios.

The results reported in panel B of Table 6 are largely similar to those in panel A. For example, the means of estimated $\beta_{2,i}$ in every sector are 0.70 for the BC model and below 0.76 for LS. On the other hand, the means are much closer to one for the other three models. Furthermore, the Merton-based mean estimate is the largest among the five model-based mean estimates for three sectors (out of seven), including 1.33 for "communication," 0.92 for "materials," and 1.43 for "technology," and the second largest for the remaining four sectors. In terms of the regression R^2, it is 28.1% for Merton, 11.9% for BC, 13.2% for LS, 30.0% for DEJD, and 18.6% for CDG. Note that although the R^2 under CDG is not the lowest here, it is still much lower than the R^2 value under either Merton or DEJD.

To summarize, while the results of the test of Hypothesis H1 favor the Merton, DEJD, and CDG models (in ascending order), the first two rank notably higher than CDG based on the regression R^2. As a low R^2 value suggests that the underlying model is unable to effectively replicate the variation in CDS contract values, the actual hedging performance of the same model may also be affected negatively. As such, the Merton and DEJD models may provide better hedging performance than does the CDG model. Furthermore, given that the Merton implied sensitivity is more reasonable than the DEJD implied one (e.g., for B and CCC names), the Merton model may provide better hedging performance than the DEJD model. In the subsection that follows we investigate which of the five candidate models delivers the most robust hedging performance.

6.5.2 Evidence on Hedging Effectiveness

Suppose that in month t, an investor hedges a single-name CDS with the underlying equity and makes no additional trades until the end of $t+1$.[11] At $t+1$, the position is closed out and the hedging error over the one-month period is computed as

$$\epsilon_t = V_{t+1}^{cds} - h_{E,t}^{cds} r_{t+1}^E,$$

where the hedge ratio $h_{E,t}^{cds}$ is as defined in Eq. (11), and we make use of the fact that a CDS contract is worth close to zero when it is first initiated ($V_t^{cds} = 0$).

Assume that the investor's objective is to minimize the monthly volatility of the hedged single-name CDS. Following Bertsimas, Kogan, and Lo (2000), we use root-mean-squared hedging error (RMSE) as the summary statistic for hedging errors over our sample period. The RMSE is equal to the standard deviation when the mean hedging error is zero. For comparison, we also compute the RMSE of the short CDS position when the CDS contract

[11] In an untabulated analysis, we also examined the performance of hedging CDS portfolio positions, with the portfolios formed based on the rating/sector category. These results are not reported as the relative performance among structural models does not change; as expected, the absolute hedging effectiveness increases because the hedging loss from one single name in the portfolio may be offset by the hedging gain from another.

is not hedged ($h^{cds}_{E,t} = 0$), denoted $RMSE^{\mathcal{U}}$. One measure of hedging effectiveness of model $\mathcal{M}$ calculates the reduction in the RMSE as a result of hedging as the following:

$$H_{\text{Eff}} = 1 - \frac{RMSE^{\mathcal{M}}}{RMSE^{\mathcal{U}}}.$$

Note that if hedge ratios implied from a particular model substantially increase volatility relative to the unhedged position, then H_{Eff} is negative.

Panel A of Table 7 presents the results on the hedging performance of firm-specific hedge ratios (i.e., hedge ratios not smoothed over a given rating group or a given sector) under the five structural models. Surprisingly, among these models the Merton H_{Eff} is the highest (7.0%), indicating that the Merton-implied hedge ratio achieves the largest reduction in the RMSE. The CDG model also has a significantly positive overall H_{Eff} (3.5%). In contrast, the overall H_{Eff} is highly negative for both the BC and LS models, implying that the hedged position—using hedge ratios derived from the two models—is much more volatile than the unhedged position. The overall negative H_{Eff} for the DEJD model has a great deal to do with the BB-rated names.

Consider next the hedging performance of the Merton and CDG models by credit ratings or sectors. Note that the Merton H_{Eff} is significantly positive for BB and B names only and that the CDG H_{Eff} is significantly positive for BB names only. On the other hand, out of the seven different sectors, the Merton H_{Eff} is significantly positive for six of them and the CDG H_{Eff} for two. These results together indicate that the Merton hedge ratio is more effective by sectors than by credit ratings.

Why is the overall H_{Eff} so negative for the BC and LS models? One possible reason is that the use of unsmoothed hedge ratios leads to dramatic increases in volatility. Indeed, we observe from Table 6 that for those rating or sector groups with a larger number of firms, the (rating- or sector-specific) average hedge ratios tend to be more aligned with their empirical counterparts. This result suggests that smoothing within a credit rating or industry group could lower the impact of uncertainty in the firm-by-firm estimation, as advocated by Schaefer and Strebulaev (2008). As such, using smoothed hedge ratios (i.e., either rating- or sector-specific (average) hedge ratios) should help mitigate this so-called "hedging crash risk."

Panel B of 7 reports the results on hedging performance of rating-specific hedge ratios. A comparison with panel A of the table indicates that the overall H_{Eff} in panel B is much less negative for the BC, LS, and DEJD models and, in fact, becomes statistically insignificant for the latter two models.[12] Although CDG's overall H_{Eff} also increases from 3.5% to 5.8%, it is not significantly different from zero. On the other hand, the Merton overall H_{Eff} increases from 7.0% to 9.9% and remains highly significant.

The hedging performance in individual rating groups also improves. For instance, the Merton H_{Eff} is now significantly positive for five out of seven groups (only two out of seven in panel A). For the BC model, its H_{Eff} for the BBB group, for example, increases from -90.3 (highly significant) in panel A to -1.82 (no longer significant) in panel B. For the LS model, its H_{Eff} for the BBB group also increases from a highly significant -113.3 in panel A to an insignificant -2.06 in panel B.

Results on hedging performance of sector-specific average hedge ratios, reported in panel C of Table 7, provide similar evidence as those in panel B do. Consider the overall H_{Eff} first. Note that again, H_{Eff} is much less negative for the BC, LS, and DEJD models than its counterparts in panel A, although it is still significant for the BC and DEJD models.[13] The CDG H_{Eff} is more positive and still significantly different from zero. The Merton H_{Eff} also increases slightly and remains highly significant. Overall, judging from the whole sample, averaging hedge ratios by ratings is more effective than averaging by industry in improving the hedging performance.

Next, consider H_{Eff} for individual sectors. For example, the LS H_{Eff} for "industrial" increases from -103.6 in panel A to -7.48 (albeit still significant) in panel B. The CDG H_{Eff} is now significantly positive for five sectors, as opposed to two sectors in panel A.

In summary, the results based on both the full sample and rating- or sector-specific subsamples in Table 7 provide strong evidence that using smoothed hedge ratios helps

[12] Why is the BC overall H_{Eff} still large and negative with smoothed hedge ratios? The reason is that the BC model-implied hedge ratios are striking for certain firms in the sample. In an untabulated analysis we find that these firms have an estimated default boundary K/F ranging from 1.26 to 1.54. When the asset value is close to this artificial boundary, the equity value becomes insensitive to the asset value. A low $\partial E_t/\partial A_t$ inflates the model-implied equity sensitivity of the CDS spread.

[13] The overall negative H_{Eff} for the DEJD model is mainly caused by a BB-rated technology firm. When this firm is excluded from the sample, the hedging performance of the DEJD model is generally comparable to that of the CDG model (untabulated).

improve the hedging performance. Furthermore, based on the hedging performance, the top three ranked models are the Merton, CDG and DEJD models.

We should note that while the analysis of hedging effectiveness presented here corresponds to an out-of-sample test of hedge ratios, the estimates of model parameters make use of the full sample. In an untabulated analysis, we examine the hedging performance for two- and seven-year CDS contracts (which are not included in the GMM estimation) and find that the results are consistent with those using the five-year CDS. In particular, the ranking of the five models based on the their hedging performance remains the same. That is, our findings are robust to the aforementioned look-ahead bias.

6.6 Model-Implied Default Probabilities

The discussion so far has focused on the implications of structural models for variables under the risk-neutral measure. In this subsection, we examine model-implied $\mathbb{P}$-measure default probabilities. For comparison, we also include model-implied default probabilities under the (risk-neutral) $\mathbb{Q}$-measure.

As an important determinant of CDS spreads, risk-neutral default probabilities are straightforward to calculate using an estimated model. In order to calculate real default probabilities, we need to specify the dynamics of the underlying variables under the $\mathbb{P}$-measure and then estimate those $\mathbb{P}$-measure parameters. The GMM-based estimation of such parameters, however, requires that $\mathbb{P}$-measure moment conditions be specified. We do not pursue this approach in this analysis. Instead, we calibrate the $\mathbb{P}$-measure parameters in the analysis that follows when it is necessary.

As a result, for illustration we focus on the Black and Cox (1976) model—the simplest one among the three candidate models with a flat barrier—in the analysis that follows. Given the specification of the BC model under $\mathbb{Q}$, its specification under $\mathbb{P}$ involves only one extra parameter, the asset risk premium $\pi_v \equiv \mu_v - r$, where μ_v is the expected asset growth rate. We calibrate π_v using the formula, $\mu_v - r = \sigma_v \times SR_v$, where SR_v denotes the asset Sharpe ratio (equal to the equity Sharpe ratio under the model). To this end, we set SR_v to 0.23, the equity Sharpe ratio of a median firm according to Chen, Collin-Dufresne, and Goldstein (2008), and then use firm-specific asset volatilities estimated earlier in Section 6.2 to calibrate firm-specific asset risk premiums.

Figure 8 plots the time series and term structure of the BC model-implied default probabilities under either the $\mathbb{Q}$ measure (panel A) or the $\mathbb{P}$ measure (panel B) over the full sample period. A comparison of panel A and Figure 1 indicates that the BC model fails to capture the surface of CDS spreads, given that the model assumes a constant recovery rate. As expected, the default probabilities under $\mathbb{Q}$ are markedly higher than their counterparts under $\mathbb{P}$. Nonetheless, both panels show a spike in late 2002, consistent with Figure 1.

We can also compare the average model-implied real default probability with the average (historical) default rate for a given rating group. For the latter, we use the average issuer-weighted cumulative default rates by rating categories over 1920–2004 calculated by Moody's. Figure 9 plots the term structures of average default rates (solid line), the BC model-implied default probabilities under the $\mathbb{Q}$ measure (blue dashed line) as well as the $\mathbb{P}$ measure (red dotted line), for three different rating groups, single A (panel A), BBB (panel B), and BB (panel C). The AAA-A group is not considered here because, first, we do not have Moody's average default rates for the AAA-A group and secondly, the AAA-A group in our sample is dominated by the single A firms. Panel C includes only the BB names instead of the CCC-BB group for the similar reason.

We make two observations from Figure 9. First, the BC model fits the Moody's average default rates well for A-rated names. The implication of this result is that the evidence based on single A firms in our sample is consistent with the notion of the credit spread puzzle: the model matches the average default rates but it underpredicts the CDS spreads. Second, the model underfits the average default rates for both BBB and BB names, especially at long horizons. To some extent, this result is not surprising given that on average, the model noticeably underestimates the CDS spreads for BBB and BB names over the full sample. For the model to match the historical averages the period 1920–2004, we need higher asset volatility, default boundary, or both (than the estimates reported in Table 3). Such parameter values also allow the model to fit the observed CDS spreads for BBB and BB names better, largely consistent with the credit spread puzzle.

7. Conclusions

Empirical studies of structural credit risk models are usually carried out using calibration, rolling window estimation, or regression analysis. This paper proposes a GMM-based specification test of these models. This alternative method allows us to directly estimate structural models, as well as test whether all the restrictions of the model are satisfied, among other things.

For illustration, we apply the proposed specification test to five representative structural models using data on the term structure of CDS spreads and realized equity volatility (estimated with high frequency intraday data). We conduct the test using a sample of industrial firms over a post dot-com bubble and pre-financial crisis period that nonetheless includes some relatively high credit risk episodes. The test results show that the Merton (1974) model and the two diffusion-based constant-barrier models are all strongly rejected by the proposed specification test. However, the results also indicate that incorporating jumps or stationary leverage into a barrier model improves the overall fit of CDS spreads and equity volatility. Nonetheless, all five models have difficulty capturing the dynamic behavior of both equity volatility and CDS spread curves, especially for investment-grade names. On the other hand, our results demonstrate that these models have a much better ability to explain the average sensitivity of CDS spreads to equity return than their ability to explain the average CDS spread and equity volatility. Surprisingly, we also find that the Merton (1974) model provides the best hedging performance among all five models.

Overall, the main findings of this study, together with those of Bao and Pan (2013) on excess corporate bond return volatility, suggest a need for new structural models that can explain not only the credit spread puzzle but also the second moment variables. Another line of inquiry worth pursuing is to conduct a more rigorous and comprehensive analysis of finite sample properties of the GMM test proposed in this study.

Table 1: Summary Statistics on CDS Spreads and the Underlying Names

This table reports summary statistics on the 93 firms, by ratings (Panel A) and sectors (Panel B), that underlie the credit default swap (CDS) contracts in the entire sample. Rating is the average of Moody's and Standard & Poor's ratings. Equity volatility is estimated using 5-minute intraday returns. Leverage ratio is the total liability divided by the total asset which is equal to total liability plus market equity. Asset payout ratio is the weighted average of dividend payout and interest expense over the total asset. Recovery rate is the quoted recovery rate accompanied with the CDS premium from the dealer-market. CDS spreads have 1-, 2-, 3-, 5-, 7-, and 10-year maturities over the period from January 2002 to December 2004.

Panel A1: Firm Characteristics by Credit Ratings

Credit rating	Sample firms number	Sample firms percentage	Equity volatility (%)	Leverage ratio (%)	Asset payout (%)	Recovery rate (%)
AAA	1	1.08	36.36	63.71	2.22	40.88
AA	6	6.45	31.50	20.92	1.53	40.92
A	25	26.88	32.51	38.15	2.02	40.57
BBB	45	48.39	35.54	51.84	2.26	40.73
BB	11	11.83	47.19	57.76	2.15	39.51
B	4	4.30	83.23	72.61	2.28	38.23
CCC	1	1.08	81.94	93.93	2.89	26.57
Overall	93	100.00	38.40	48.34	2.14	40.30

Panel A2: Average CDS Spreads (%) by CDS Maturities and Ratings

	Maturity of CDS					
	1-year	2-year	3-year	5-year	7-year	10-year
AAA	0.23	0.28	0.32	0.43	0.45	0.49
AA	0.12	0.13	0.15	0.20	0.23	0.28
A	0.25	0.29	0.32	0.39	0.43	0.49
BBB	0.74	0.79	0.86	0.94	0.98	1.05
BB	2.62	2.74	2.84	2.90	2.92	2.92
B	7.52	7.20	7.51	7.25	7.01	6.79
CCC	25.26	22.99	20.91	18.81	18.03	17.31
Overall	1.34	1.36	1.40	1.44	1.45	1.49

Panel A3: Std. Dev. of CDS Spreads (%) by CDS Maturities and Ratings

	1-year	2-year	3-year	5-year	7-year	10-year
AAA	0.17	0.19	0.21	0.25	0.23	0.24
AA	0.07	0.07	0.07	0.09	0.09	0.10
A	0.23	0.27	0.24	0.25	0.24	0.26
BBB	0.96	0.96	0.96	0.91	0.89	0.84
BB	2.72	2.75	2.59	2.35	2.28	2.14
B	8.67	6.19	7.61	6.12	5.90	5.25
CCC	24.96	19.40	16.48	13.65	12.68	11.81
Overall	4.43	3.78	3.62	3.18	3.04	2.85

Table 1 (continued)

Panel B1: Firm Characteristics by Sectors

Sector	Sample firms number	Sample firms percentage	Equity volatility (%)	Leverage ratio (%)	Asset payout (%)	Recovery rate (%)
Communications	6	6.45	48.72	42.93	1.99	40.14
Consumer Cyclical	32	34.41	38.95	48.56	2.01	40.45
Consumer Staple	14	15.05	33.77	41.68	2.24	40.87
Energy	8	8.60	39.93	53.89	2.47	40.05
Industrial	18	19.35	40.24	53.90	2.01	39.90
Materials	11	11.83	32.85	49.34	2.73	41.35
Technology	4	4.30	45.22	40.20	1.29	38.95
Overall	93	100.00	38.68	48.39	2.14	40.39

Panel B2: Average CDS Spreads (%) by CDS Maturities and Sectors

	Maturity of CDS: 1-year	2-year	3-year	5-year	7-year	10-year
Communications	2.04	1.99	2.09	2.23	2.16	2.10
Consumer Cyclical	1.57	1.58	1.58	1.61	1.62	1.66
Consumer Staple	0.74	0.81	0.86	0.92	0.94	0.98
Energy	1.58	1.38	1.53	1.43	1.47	1.48
Industrial	1.29	1.38	1.41	1.46	1.48	1.53
Materials	0.92	0.96	1.03	1.10	1.14	1.20
Technology	1.38	1.43	1.48	1.48	1.51	1.52
Overall	1.34	1.36	1.40	1.44	1.45	1.49

Panel B3: Std. Dev. of CDS Spreads (%) by CDS Maturities and Sectors

	1-year	2-year	3-year	5-year	7-year	10-year
Communications	4.82	4.13	4.58	4.74	4.33	3.80
Consumer Cyclical	6.19	5.25	4.65	4.06	3.85	3.65
Consumer Staple	2.08	2.21	2.18	2.10	2.02	1.92
Energy	5.60	3.66	4.80	3.32	3.45	3.14
Industrial	2.36	2.54	2.34	2.16	2.09	2.07
Materials	1.46	1.42	1.43	1.39	1.38	1.34
Technology	2.20	2.17	2.12	1.82	1.74	1.59
Overall	4.43	3.78	3.62	3.18	3.04	2.85

Table 2: Specification Test of Structural Credit Risk Models

This table reports the omnibus GMM test results of overidentifying restrictions under each of five structural models considered. The five moment conditions used in the test are constructed based on the pricing relationship for 1-, 3-, 5- and 10-year credit default swap (CDS) spreads and for the equity volatility estimated based on 5-minute intraday data. The five model specifications considered include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001, CDG hereafter), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002). Data used in the test are monthly CDS spreads and equity volatility from January 2002 to December 2004.

	# of Firms	Structural Credit Risk Models Estimated														
		Merton			Black-Cox			Longstaff-Schwartz			DEJD			CDG		
		Chi-Square Values														
d.o.f.			4			3			3			2			1	
Mean			16.59			14.79			14.41			9.32			3.83	
Percentiles		*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95
		12.59	17.12	17.92	12.03	15.08	16.26	13.66	14.53	14.62	1.57	9.36	15.73	0.01	2.21	13.27
Sig. level		0.01	0.05	0.10	0.01	0.05	0.10	0.01	0.05	0.10	0.01	0.05	0.10	0.01	0.05	0.10
		Panel A: Number of Firms with the Model Being not Rejected: by Ratings														
AAA	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0
AA	6	0	0	0	0	0	0	0	0	0	2	1	1	4	4	3
A	25	0	0	0	0	0	0	0	0	0	10	8	6	22	22	21
BBB	44	2	0	0	2	0	0	6	2	1	22	7	4	36	29	23
BB	12	3	0	0	2	1	1	4	2	1	4	1	0	6	4	3
B	4	0	0	0	2	0	0	1	1	0	2	2	1	4	4	2
CCC	1	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
		Panel B: Number of Firms with the Model Being not Rejected: by Sectors														
Communications	6	1	0	0	2	0	0	1	0	0	3	0	0	5	5	4
Consumer Cyclic	32	1	0	0	0	0	0	3	1	0	16	8	4	21	18	15
Consumer Stable	14	0	0	0	0	0	0	0	0	0	5	2	2	11	10	7
Energy	8	0	0	0	1	0	0	1	1	0	4	3	1	6	5	4
Industrial	18	1	0	0	1	1	1	4	2	2	9	4	3	16	14	11
Materials	11	1	0	0	1	0	0	2	1	0	5	3	3	10	9	9
Technology	4	1	0	0	1	0	0	1	1	0	0	0	0	3	2	2
Total	93	5	1	0	6	1	1	12	6	2	42	20	13	72	63	52

Table 3: Parameter Estimation of Structural Credit Risk Models

This table reports the GMM estimation results of the model parameters in each of five structural models. The five moment conditions used in the test are constructed based on the pricing relationship for 1-, 2-, 5- and 10-year CDS spreads and for the equity volatility estimated based on 5-minute intraday data. The five model specifications include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001, CDG hereafter), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002). Panel A reports the asset volatility parameter estimate σ_v in all five models, Panel B reports the default boundary estimate K in three barrier type models, and Panel C reports jump intensity estimate λ^Q in the DEJD model and dynamic leverage parameters, κ_ℓ, ν, and ϕ, in the CDG model.

Panel A: Estimates of the Asset Volatility under Different Structural Models

	# of Firms	Structural Credit Risk Models Estimated														
Total	93	Merton			Black-Cox			Longstaff-Schwartz			DEJD			CDG		
Mean			0.154			0.168			0.177			0.160			0.199	
Std. Dev.			(0.007)			(0.007)			(0.090)			(0.010)			(0.042)	
Percentiles		*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95	*p*5	*p*50	*p*95
		0.070	0.135	0.337	0.097	0.151	0.274	0.061	0.153	0.407	0.075	0.154	0.252	0.098	0.170	0.337
Asymptotic SEs	(0.002)	(0.006)	(0.014)	(0.003)	(0.006)	(0.016)	(0.006)	(0.047)	(0.228)	(0.003)	(0.006)	(0.031)	(0.005)	(0.011)	(0.031)	
AAA	1	0.133	0.133	0.133	0.100	0.100	0.100	0.160	0.160	0.160	0.141	0.141	0.141	0.114	0.114	0.114
AA	6	0.053	0.075	0.106	0.156	0.243	0.267	0.153	0.291	0.380	0.154	0.186	0.239	0.134	0.242	0.339
A	25	0.068	0.112	0.168	0.090	0.149	0.203	0.088	0.153	0.250	0.128	0.164	0.221	0.114	0.173	0.325
BBB	44	0.095	0.137	0.222	0.102	0.145	0.216	0.058	0.139	0.227	0.072	0.148	0.224	0.077	0.166	0.276
BB	12	0.111	0.198	0.408	0.114	0.194	0.388	0.054	0.205	0.645	0.076	0.135	0.392	0.104	0.206	0.554
B	4	0.263	0.361	0.399	0.183	0.297	0.351	0.072	0.434	0.602	0.075	0.175	0.264	0.105	0.349	0.473
CCC	1	0.369	0.369	0.369	0.270	0.270	0.270	0.054	0.054	0.054	0.054	0.054	0.054	0.042	0.042	0.042
Communications	6	0.069	0.184	0.399	0.113	0.151	0.335	0.074	0.181	0.412	0.138	0.161	0.264	0.107	0.292	0.451
Consumer Cyclic	32	0.091	0.150	0.309	0.097	0.167	0.268	0.045	0.153	0.290	0.055	0.150	0.237	0.042	0.167	0.325
Consumer Stable	14	0.053	0.081	0.239	0.094	0.146	0.265	0.106	0.148	0.557	0.085	0.159	0.237	0.106	0.171	0.307
Energy	8	0.105	0.134	0.340	0.112	0.158	0.206	0.072	0.150	0.240	0.097	0.142	0.216	0.113	0.161	0.296
Industrial	18	0.097	0.135	0.403	0.091	0.125	0.378	0.066	0.131	0.583	0.086	0.149	0.343	0.095	0.165	0.526
Materials	11	0.081	0.110	0.222	0.107	0.151	0.230	0.108	0.155	0.201	0.101	0.148	0.276	0.115	0.187	0.243
Technology	4	0.098	0.169	0.304	0.176	0.209	0.275	0.198	0.245	0.441	0.174	0.179	0.289	0.233	0.248	0.493

Table 3 (continued)

Panel B: Estimate of the Default Boundary

	# of Firms	Structural Credit Risk Models Considered								
Total	93	Black-Cox			Longstaff-Schwartz			DEJD		
Mean		1.176			1.161			0.830		
Std. Dev.		(0.145)			(0.274)			(0.183)		
Percentiles		$p5$	$p50$	$p95$	$p5$	$p50$	$p95$	$p5$	$p50$	$p95$
		0.640	1.055	1.923	0.536	1.049	2.018	0.419	0.752	1.734
Asymptotic SEs		(0.006)	(0.134)	(0.217)	(0.020)	(0.173)	(0.859)	(0.020)	(0.163)	(0.316)
AAA	1	0.971	0.971	0.971	1.086	1.086	1.086	0.723	0.723	0.723
AA	6	0.844	0.905	2.296	0.751	1.034	2.442	0.807	1.553	1.773
A	25	0.887	1.362	2.425	0.751	1.180	2.449	0.304	0.886	1.904
BBB	44	0.638	1.072	1.685	0.597	1.057	1.835	0.443	0.696	1.174
BB	12	0.655	0.867	1.782	0.430	0.921	1.783	0.422	0.672	1.759
B	4	0.550	0.793	0.983	0.333	0.718	1.004	0.380	0.538	0.700
CCC	1	0.959	0.959	0.959	1.011	1.011	1.011	0.706	0.706	0.706
Communications	6	0.612	1.295	1.675	0.449	1.208	1.846	0.087	0.614	1.137
Consumer Cyclic	32	0.648	1.094	2.199	0.618	1.174	2.211	0.501	0.749	1.570
Consumer Stable	14	0.606	1.007	2.740	0.417	0.894	2.813	0.474	0.822	1.980
Energy	8	0.638	0.938	1.951	0.417	0.925	2.094	0.350	0.656	1.862
Industrial	18	0.660	1.019	1.840	0.635	1.033	1.813	0.405	0.710	0.953
Materials	11	0.865	1.062	1.513	0.756	1.150	1.657	0.427	0.807	1.025
Technology	4	0.655	0.958	1.630	0.548	0.928	1.636	0.635	0.775	1.767

Panel C: Estimates of Other Parameters in the DEJD and CDG Models

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	# of Firms	Structural Credit Risk Models Considered											
Total	93	DEJD			Collin-Dufresne and Goldstein								
Parameter		λ^Q			κ_ℓ			ν			ϕ		
Mean		0.181			15.155			0.222			2.829		
Std. Dev.		{0.078}			{3.258}			{0.274}			{2.070}		
Percentiles		$p5$	$p50$	$p95$	$p5$	$p50$	$p95$	$p5$	$p50$	$p95$	$p5$	$p50$	$p95$
		0.042	0.126	0.499	0.446	15.347	35.466	0.069	0.163	1.180	-0.103	1.878	6.242
Asymptotic SEs		(0.009)	(0.029)	(0.132)	(0.007)	(0.062)	(0.439)	(0.003)	(0.008)	(0.137)	(0.048)	(0.181)	(1.867)
AAA	1	0.119	0.119	0.119	15.042	15.042	15.042	0.106	0.106	0.106	1.184	1.184	1.184
AA	6	0.057	0.092	0.227	1.608	17.715	22.097	0.185	0.293	1.988	0.359	3.142	36.208
A	25	0.034	0.113	0.277	10.189	16.826	35.489	0.099	0.173	0.555	1.352	2.279	10.199
BBB	44	0.054	0.123	0.465	8.717	15.357	35.489	0.068	0.142	0.261	-0.095	1.736	2.952
BB	12	0.008	0.209	0.483	0.047	1.414	20.708	-4.117	0.209	1.158	-12.185	1.367	11.763
B	4	0.420	0.493	0.981	0.476	5.191	8.877	0.069	0.261	1.017	-0.797	1.581	6.336
CCC	1	0.580	0.580	0.580	-0.021	-0.021	-0.021	1.566	1.566	1.566	37.416	37.416	37.416
Communications	6	0.044	0.166	0.420	1.905	12.767	15.833	0.191	0.255	1.389	1.428	3.091	29.644
Consumer Cyclic	32	0.060	0.151	0.559	0.126	15.434	33.934	0.069	0.164	1.946	-0.099	1.876	32.980
Consumer Stable	14	0.043	0.114	0.468	2.982	17.280	35.489	0.073	0.148	0.295	0.148	1.862	3.507
Energy	8	0.040	0.118	0.469	8.877	14.580	19.271	0.090	0.136	0.277	-0.797	1.340	3.508
Industrial	18	0.043	0.107	0.713	0.647	15.437	35.489	0.069	0.146	0.888	-7.485	1.743	2.796
Materials	11	0.057	0.096	0.441	0.062	17.096	24.548	-4.351	0.159	0.277	-0.025	1.908	5.671
Technology	4	0.001	0.088	0.114	0.406	8.633	16.944	0.195	0.418	1.209	-9.763	2.566	12.435

Table 4: CDS Pricing Errors in Structural Credit Risk Models

This table reports the pricing errors of CDS spreads under each of five structural models. Pricing errors are calculated as the average, absolute, average percentage, and absolute percentage differences between the model implied and observed spreads, across six maturities, 1, 2, 3, 5, 7, and 10 years, and monthly observations from January 2002 to December 2004. The five model specifications include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2012).

Firms		CDS Pricing Errors in Five Different Models									
by ratings/sectors	number	**Merton**	**BC**	**LS**	**DEJD**	**CDG**	**Merton**	**BC**	**LS**	**DEJD**	**CDG**
		Panel A: Average Pricing Error (%)					Panel B: Absolute Pricing Error (%)				
Overall	93	0.37	-0.91	-0.71	-0.44	-0.18	1.54	0.99	0.98	0.75	0.78
AAA	1	-0.14	-0.30	-0.28	0.00	-0.11	0.24	0.30	0.28	0.19	0.20
AA	6	-0.19	-0.12	-0.16	-0.06	-0.03	0.19	0.15	0.16	0.09	0.11
A	25	-0.31	-0.25	-0.25	-0.08	-0.03	0.34	0.28	0.29	0.17	0.18
BBB	44	0.11	-0.63	-0.61	-0.32	0.00	1.23	0.66	0.68	0.45	0.59
BB	12	0.16	-1.65	-1.60	-0.10	-0.07	2.46	1.82	1.95	1.47	1.41
B	4	6.39	-4.34	-4.24	-3.62	-0.89	8.05	4.95	4.68	4.28	3.31
CCC	1	11.55	-12.95	4.00	-8.82	-10.92	17.14	12.96	10.26	9.94	11.43
Communications	6	-0.50	-1.61	-1.84	-1.51	-0.28	1.29	1.62	1.86	1.53	1.08
Consumer Cyclic	32	1.02	-1.09	-0.59	-0.50	-0.54	2.27	1.10	1.08	0.72	0.88
Consumer Stable	14	0.43	-0.64	-0.67	-0.13	-0.11	1.06	0.67	0.72	0.31	0.34
Energy	8	1.47	-1.04	-0.71	-0.71	-0.20	2.35	1.07	0.78	0.82	0.81
Industrial	18	-0.29	-0.61	-0.53	-0.53	0.08	0.85	0.92	0.90	0.70	0.71
Materials	11	-0.28	-0.69	-0.77	-0.41	0.60	0.81	0.70	0.80	0.54	0.94
Technology	4	-1.17	-1.19	-0.89	1.33	-0.56	1.17	1.19	0.94	1.92	0.97
		Panel C: Average Percentage Pricing Error (%)					Panel D: Absolute Percentage Pricing Error (%)				
Overall	93	-29.62	-70.91	-68.94	-11.88	24.42	114.29	76.20	78.17	45.63	68.88
AAA	1	-6.60	-82.04	-74.13	47.96	3.40	70.69	82.04	75.42	80.03	56.99
AA	6	-100.00	-67.72	-85.95	-21.09	-3.91	100.00	82.60	86.11	44.56	69.12
A	25	-82.60	-71.86	-68.88	-1.95	9.69	97.29	78.14	80.27	47.33	55.39
BBB	44	-25.54	-72.85	-69.50	-17.29	40.35	119.78	76.84	78.82	44.37	80.26
BB	12	15.92	-70.77	-69.28	-6.81	16.01	111.45	72.73	76.82	43.01	58.47
B	4	182.82	-50.96	-50.61	-29.71	33.91	196.57	62.82	59.60	51.82	64.48
CCC	1	117.78	-50.82	-7.35	-16.28	-54.47	131.60	50.85	42.83	37.14	58.59
Communications	6	-62.16	-76.83	-77.03	-39.66	31.97	82.63	77.83	79.42	51.39	87.03
Consumer Cyclic	32	14.04	-72.77	-72.08	-6.97	6.22	154.04	75.83	80.02	43.77	60.93
Consumer Stable	14	-55.69	-71.10	-64.90	-17.18	3.18	107.27	80.71	79.44	38.03	43.72
Energy	8	-5.28	-66.81	-76.71	-23.08	17.52	133.16	71.67	78.17	38.10	50.46
Industrial	18	-51.63	-66.06	-56.16	-19.15	41.55	74.67	76.29	75.49	45.10	71.85
Materials	11	-66.48	-70.35	-73.29	9.67	86.40	85.74	72.67	75.50	58.27	125.59
Technology	4	-87.25	-77.93	-75.78	4.83	-0.78	87.25	79.34	76.47	61.09	60.87

Table 5: Fitting Errors of Equity Volatility in Structural Credit Risk Models

This table reports the fitting errors of equity volatility under each of five structural models. Fitting errors are reported as the average, absolute, average percentage, and absolute percentage differences between the model implied and observed annualized equity volatility, across monthly observations from January 2002 to December 2004. The fitted errors of equity volatility are calculated in a similar fashion. The five model specifications include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2012).

Firms		Fitting Errors of Equity Volatility in Five Different Models									
by ratings/sectors	number	Merton	BC	LS	DEJD	CDG	Merton	BC	LS	DEJD	CDG
		Panel A: Average Fitting Error (%)					Panel B: Absolute Fitting Error (%)				
Overall	93	5.32	-6.36	-0.77	-7.21	-0.53	26.11	12.09	17.01	11.61	11.87
AAA	1	-3.69	1.03	7.31	1.83	-5.03	12.04	14.42	15.55	13.56	11.81
AA	6	-23.91	-2.29	2.84	-7.97	-0.99	23.91	10.46	13.32	9.91	9.01
A	25	-13.77	-4.95	-6.78	-6.26	-1.15	15.66	10.00	10.66	9.50	8.40
BBB	44	1.92	-5.93	-2.88	-6.56	-1.16	18.32	10.48	13.20	10.01	9.42
BB	12	11.99	-6.82	12.08	-8.81	-1.16	23.79	14.08	24.70	15.89	16.10
B	4	75.80	-31.88	29.71	-17.42	-2.24	83.67	33.62	69.56	28.69	32.70
CCC	1	455.21	15.45	-64.06	-3.47	64.65	455.21	32.11	64.06	23.46	90.07
Communications	6	-8.80	-12.79	-6.90	-16.82	-3.37	18.82	17.07	17.90	18.56	18.03
Consumer Cyclic	32	20.28	-5.89	-5.46	-7.32	1.10	40.10	11.72	16.20	11.02	12.46
Consumer Stable	14	-1.46	-4.81	10.04	-4.15	-0.90	26.77	11.04	21.15	9.50	9.09
Energy	8	12.43	-13.50	-4.03	-2.80	0.76	26.93	15.37	22.73	10.35	11.94
Industrial	18	-2.68	-4.22	0.17	-8.48	-1.68	13.29	11.34	14.82	12.19	11.05
Materials	11	-7.08	-2.26	1.28	-4.84	-2.92	11.74	9.03	10.30	8.70	9.27
Technology	4	-13.54	-12.47	4.63	-12.17	1.19	18.44	16.37	24.39	21.18	18.43
		Panel C: Average Pct Fitting Error (%)					Panel D: Absolute Pct Fitting Error (%)				
Overall	93	7.09	-5.44	6.40	-8.96	7.33	58.29	27.88	40.49	25.53	28.41
AAA	1	5.03	21.40	39.47	22.23	0.60	31.98	43.20	51.85	41.33	30.02
AA	6	-72.12	6.57	25.67	-15.04	6.61	72.12	31.67	45.25	25.31	27.39
A	25	-37.18	-4.21	-11.83	-8.99	5.20	44.10	28.02	29.56	24.74	25.49
BBB	44	12.06	-7.42	1.02	-9.32	6.11	48.81	26.10	35.00	24.02	25.59
BB	12	36.98	-4.59	39.25	-6.92	8.54	53.62	27.91	58.90	29.27	34.20
B	4	120.65	-28.54	64.24	-11.47	21.05	125.78	32.33	95.26	31.34	45.24
CCC	1	559.59	33.77	-75.23	-1.53	55.91	559.59	46.11	75.23	29.67	92.76
Communications	6	-13.47	-11.92	-10.51	-21.16	10.67	38.70	29.91	32.49	29.44	38.85
Consumer Cyclic	32	37.53	-6.48	-4.13	-11.58	7.48	84.72	27.37	38.63	24.56	27.90
Consumer Stable	14	-20.12	-0.98	26.74	-3.49	5.77	67.18	30.26	50.61	25.48	26.17
Energy	8	19.65	-18.90	15.72	-0.47	11.07	54.35	27.63	53.61	24.22	28.89
Industrial	18	-2.65	-0.80	2.79	-9.97	6.66	32.14	27.43	34.52	25.08	25.63
Materials	11	-18.31	0.83	11.02	-5.59	0.41	33.54	25.44	31.32	22.54	25.54
Technology	4	-21.83	-14.32	29.84	-10.53	21.20	38.76	29.83	57.78	40.55	44.02

Table 6: Tests of Model-Implied Sensitivities

This table reports results from the following time-series regression

$$\Delta\widetilde{\text{cds}}(t,t+5)_i = \alpha_i + \beta_{1,i}\Delta r^{10y}_{f,t} + \beta_{2,i}\overline{\Delta}^{cds}_{E,i,t}\, rx^{E}_{i,t} + u_{it}$$

where $\Delta\widetilde{\text{cds}}(t,t+5)_i$ denotes the monthly change in firm-i's 5-year CDS premium; rf^{10y}_t the monthly change in the 10-year interest swap rates; $rx^E_{i,t}$ the monthly excess returns on firm-i's equity; and $\overline{\Delta}^{cds}_{E,i,t}$ denotes the month-t average of model-implied sensitivities across firms in the same rating or industry category as firm i for a given structural model. For each month, these firm specific hedge ratios are averaged out within either rating (panel A) or industry (panel B) categories. The reported coefficient values are averaged estimates of $\beta_{2,i}$ across firms; in angle brackets is reported the number of firms where $\beta_{2,i} = 1$ is not rejected at the 5% significance level for each of the five models; the statistics in brackets are regression R^2s. The five model specifications include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion model used in Huang and Huang (2012). The sample period is from January 2002 to December 2004.

	Panel A: Rating Specific Average Sensitivities							Panel B: Sector Specific Average Sensitivities						
			Models Used							Models Used				
Regression related variables	Rating	# of Firms	Merton	BC	LS	DEJD	CDG	Sector	# of Firms	Merton	BC	LS	DEJD	CDG
$\bar{\beta}_{2,i}$	AAA	1	0.92	0.75	0.73	0.87	1.25	Communications	6	1.33	0.70	0.72	1.30	1.25
# of No-Rej			< 1 >	< 0 >	< 0 >	< 1 >	< 1 >			< 6 >	< 0 >	< 4 >	< 6 >	< 4 >
R^2			[0.307]	[0.580]	[0.532]	[0.286]	[0.269]			[0.421]	[0.101]	[0.185]	[0.418]	[0.185]
$\bar{\beta}_{2,i}$	AA	6	0.70	0.70	0.72	0.70	0.73	Consumer Cyclic	32	1.00	0.70	0.73	0.99	1.01
# of No-Rej			< 0 >	< 0 >	< 1 >	< 0 >	< 4 >			< 25 >	< 0 >	< 7 >	< 26 >	< 26 >
R^2			[0.174]	[0.137]	[0.131]	[0.172]	[0.149]			[0.292]	[0.128]	[0.140]	[0.316]	[0.194]
$\bar{\beta}_{2,i}$	A	25	0.84	0.72	0.74	0.81	0.83	Consumer Stable	14	0.81	0.70	0.76	0.81	0.83
# of No-Rej			< 15 >	< 1 >	< 5 >	< 13 >	< 19 >			< 5 >	< 0 >	< 6 >	< 4 >	< 12 >
R^2			[0.272]	[0.262]	[0.270]	[0.270]	[0.193]			[0.194]	[0.149]	[0.123]	[0.201]	[0.169]
$\bar{\beta}_{2,i}$	BBB	44	1.00	0.73	0.76	0.94	1.04	Energy	8	1.16	0.70	0.67	1.23	0.74
# of No-Rej			< 41 >	< 4 >	< 6 >	< 40 >	< 35 >			< 6 >	< 0 >	< 1 >	< 6 >	< 6 >
R^2			[0.279]	[0.236]	[0.263]	[0.278]	[0.199]			[0.160]	[0.103]	[0.107]	[0.189]	[0.219]
$\bar{\beta}_{2,i}$	BB	12	1.58	0.81	0.76	1.42	0.94	Industrial	18	1.03	0.70	0.68	0.99	1.06
# of No-Rej			< 10 >	< 3 >	< 2 >	< 10 >	< 12 >			< 15 >	< 0 >	< 5 >	< 13 >	< 16 >
R^2			[0.507]	[0.385]	[0.443]	[0.506]	[0.180]			[0.268]	[0.099]	[0.139]	[0.277]	[0.133]
$\bar{\beta}_{2,i}$	B	4	2.90	0.88	0.83	2.52	1.25	Materials	11	0.92	0.70	0.70	0.90	0.88
# of No-Rej			< 4 >	< 3 >	< 3 >	< 4 >	< 4 >			< 7 >	< 0 >	< 0 >	< 7 >	< 8 >
R^2			[0.390]	[0.360]	[0.384]	[0.393]	[0.110]			[0.276]	[0.107]	[0.111]	[0.300]	[0.166]
$\bar{\beta}_{2,i}$	CCC	1	3.90	0.95	0.86	3.49	1.00	Technology	4	1.43	0.70	0.69	1.37	0.80
# of No-Rej			< 1 >	< 1 >	< 1 >	< 1 >	< 1 >			< 4 >	< 0 >	< 2 >	< 3 >	< 1 >
R^2			[0.152]	[0.089]	[0.095]	[0.171]	[0.054]			[0.596]	[0.124]	[0.109]	[0.669]	[0.423]
$\bar{\beta}_{2,i}$	Overall	93	1.12	0.74	0.76	1.05	0.96	Overall	93	1.02	0.70	0.71	1.01	0.96
# of No-Rej			< 72 >	< 12 >	< 18 >	< 69 >	< 76 >			< 68 >	< 0 >	< 25 >	< 65 >	< 73 >
R^2			[0.304]	[0.263]	[0.286]	[0.302]	[0.187]			[0.281]	[0.119]	[0.132]	[0.300]	[0.186]

Table 7: Hedging Performance of Structural Credit Risk Models

This table reports empirical results on the effectiveness of hedging changes in CDS spreads with three types of hedge ratios. The first type (panel A) is firm specific hedge ratios implied from five estimated structural models: Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2012). The other two types of hedge ratios are obtained by averaging firm specific hedge ratios within either each credit rating (panel B) or each industry (panel C) category. Measure of hedging effectiveness is 1-$RMSE_h/RMSE_u$, where $RMSE_h$ ($RMSE_u$) is the root mean square error of the hedged (unhedged) position. The statistics in parenthesis are standard errors of this effectiveness obtained from 5,000 bootstrap simulations. The sample period is from January 2002 to December 2004.

		Structural Models Used									
Rating or Sector	# of Firms	Merton	BC	LS	DEJD	CDG	Merton	BC	LS	DEJD	CDG
		Panel A: Firm Specific Hedge Ratios					Panel B: Rating Specific Average Hedge Ratios				
AAA	1	-0.817	0.088	0.175	0.101	0.009	-0.817	0.088	0.175	0.101	0.009
		(0.176)	(0.833)	(0.632)	(0.085)	(0.177)	(0.176)	(0.833)	(0.632)	(0.085)	(0.177)
AA	6	0.001	-0.327	0.046	-0.095	0.018	0.030	-0.024	0.050	-0.069	0.035
		(0.050)	(0.318)	(0.251)	(0.033)	(0.070)	(0.000)	(0.035)	(0.023)	(0.041)	(0.022)
A	25	-0.067	-1.684	0.052	-0.129	0.014	0.099	-0.615	0.118	0.115	0.043
		(0.038)	(0.155)	(0.119)	(0.016)	(0.034)	(0.021)	(0.141)	(0.022)	(0.030)	(0.009)
BBB	44	0.005	-90.298	-113.276	0.001	0.022	0.089	-1.818	-2.057	0.109	0.053
		(0.018)	(0.116)	(0.093)	(0.012)	(0.027)	(0.022)	(1.154)	(1.147)	(0.022)	(0.032)
BB	12	0.113	-2.898	-2.237	-21.019	0.184	0.260	-0.058	0.083	-1.822	0.163
		(0.042)	(0.223)	(0.176)	(0.023)	(0.050)	(0.109)	(0.092)	(0.101)	(0.543)	(0.089)
B	4	0.119	-30.461	-0.114	0.039	0.045	0.112	-13.806	0.014	0.073	0.062
		(0.064)	(0.410)	(0.308)	(0.041)	(0.088)	(0.063)	(6.826)	(0.047)	(0.022)	(0.118)
CCC	1	0.058	-9.933	-0.053	0.018	0.001	0.058	-9.933	-0.053	0.018	0.001
		(0.307)	(0.806)	(0.639)	(0.085)	(0.173)	(0.307)	(0.806)	(0.639)	(0.085)	(0.173)
Overall	93	0.070	-29.824	-23.849	-5.133	0.035	0.099	-11.389	-0.359	-0.186	0.058
		(0.016)	(0.080)	(0.053)	(0.008)	(0.018)	(0.041)	(3.628)	(0.215)	(0.112)	(0.040)
							Panel C: Sector Specific Average Hedge Ratios				
Communications	6	0.143	0.098	0.133	0.082	0.090	0.124	0.104	0.078	0.067	0.050
		(0.064)	(0.322)	(0.250)	(0.033)	(0.071)	(0.027)	(0.063)	(0.038)	(0.017)	(0.060)
Consumer Cyclic	32	0.009	-9.674	-0.011	0.017	0.004	0.050	-0.011	0.039	0.047	0.032
		(0.027)	(0.137)	(0.107)	(0.014)	(0.031)	(0.009)	(0.167)	(0.007)	(0.008)	(0.005)
Consumer Stable	14	-0.054	0.003	0.030	0.060	0.193	0.060	0.053	0.056	0.057	0.052
		(0.039)	(0.208)	(0.158)	(0.021)	(0.047)	(0.015)	(0.030)	(0.010)	(0.014)	(0.023)
Energy	8	0.096	-36.861	-0.134	0.015	0.012	0.082	-5.429	0.028	0.048	0.030
		(0.056)	(0.267)	(0.214)	(0.028)	(0.061)	(0.036)	(5.189)	(0.014)	(0.024)	(0.016)
Industrial	18	-0.056	-71.679	-103.578	-2.329	0.206	0.113	-6.520	-7.482	0.207	0.096
		(0.040)	(0.186)	(0.150)	(0.020)	(0.041)	(0.097)	(2.249)	(2.243)	(0.092)	(0.057)
Materials	11	-0.297	-4.101	0.035	0.159	-0.198	0.045	-0.055	0.181	0.146	0.107
		(0.065)	(0.228)	(0.187)	(0.024)	(0.053)	(0.069)	(0.088)	(0.087)	(0.051)	(0.037)
Technology	4	0.148	0.098	-4.252	-38.955	0.076	0.208	0.171	-0.241	-12.060	0.075
		(0.150)	(0.395)	(0.317)	(0.042)	(0.087)	(0.070)	(0.066)	(0.506)	(3.304)	(0.028)
Overall	93	0.070	-29.824	-23.849	-5.133	0.035	0.076	-3.310	-1.206	-1.179	0.042
		(0.016)	(0.080)	(0.053)	(0.008)	(0.018)	(0.018)	(1.331)	(0.738)	(0.571)	(0.023)

Table A1: Summary Statistics of Individual Names

This table reports credit ratings, 5-year credit default swap (CDS) spread, equity volatility, leverage ratio, asset payout, and recovery rate, for each of the 93 firms similar to those by ratings and sectors in Table 1.

Company	Last Rating	Five-Yr CDS (%)	Equity Volatility (%)	Leverage Ratio (%)	Asset Payout (%)	Recovery Rate (%)
Air Prods & Chems Inc	A	0.238	28.358	33.067	2.086	40.863
Albertsons Inc	BBB	0.692	35.540	54.662	3.650	41.008
Amerada Hess Corp	BB	0.817	28.458	61.871	2.929	40.081
Anadarko Pete Corp	BBB	0.427	31.244	47.816	1.688	39.439
Arrow Electrs Inc	BBB	2.175	44.325	62.279	2.259	39.269
Autozone Inc	BBB	0.708	33.269	30.222	0.827	41.977
Avon Prods Inc	A	0.230	27.128	17.924	0.998	41.353
Baker Hughes Inc	A	0.298	39.469	20.584	1.764	40.833
Baxter Intl Inc	BBB	0.493	39.739	33.159	1.739	40.526
BellSouth Corp	A	0.550	43.254	39.213	3.308	41.848
Black & Decker Corp	BBB	0.389	29.569	45.897	1.566	42.200
Boeing Co	A	0.517	36.815	56.877	1.744	39.336
BorgWarner Inc	BBB	0.572	29.766	48.270	1.285	40.623
Bowater Inc	BB	2.751	30.755	62.578	3.583	41.287
CSX Corp	BBB	0.607	29.651	69.128	2.305	40.486
Campbell Soup Co	A	0.319	27.171	36.114	2.699	40.063
Caterpillar Inc	A	0.350	32.081	57.902	1.992	40.122
Cendant Corp	BBB	1.595	42.626	59.864	1.291	39.440
Centex Corp	BBB	0.895	41.148	69.613	2.543	40.670
Clear Channel Comms Inc	BBB	1.413	45.192	35.378	1.487	40.789
Coca Cola Entpers Inc	A	0.327	34.774	68.903	2.281	40.019
Computer Assoc Intl Inc	BB	2.889	54.727	35.045	1.044	35.840
Computer Sciences Corp	A	0.565	41.122	43.578	1.182	39.763
ConAgra Foods Inc	BBB	0.470	27.510	43.829	3.516	39.320
Corning Inc	BB	5.412	80.739	41.995	1.138	36.807
Delphi Corp	BBB	1.470	40.828	77.164	1.535	40.539
Delta Air Lines Inc	CCC	18.806	81.939	93.931	2.885	26.566
Devon Engy Corp	BBB	0.732	31.487	56.495	2.281	40.513
Diamond Offshore Drilling Inc	BBB	0.488	39.213	32.696	1.701	40.833
Dow Chem Co	A	0.817	35.536	48.723	3.166	39.775
E I du Pont de Nemours & Co	AA	0.241	30.318	37.916	2.574	41.409
Eastman Kodak Co	BBB	1.317	37.618	56.431	2.550	38.839
Eaton Corp	A	0.335	27.783	42.526	1.527	40.815
Electr Data Sys Corp	BB	2.087	51.554	50.321	2.332	40.349
Eli Lilly & Co	AA	0.219	35.486	13.956	1.898	40.494
Fedt Dept Stores Inc	BBB	0.675	38.303	54.236	1.966	41.664
Ford Mtr Co	BBB	2.977	47.060	92.612	2.769	41.849
GA Pac Corp	BB	3.824	48.523	74.892	3.547	42.054
Gen Elec Co Inc	AAA	0.427	36.356	63.713	2.223	40.883
Gen Mls Inc	BBB	0.539	24.225	44.680	3.095	41.508
Gen Mtrs Corp	BBB	2.434	35.537	94.017	2.595	41.278
Gillette Co	AA	0.147	28.421	17.574	1.672	40.977
Goodrich Corp	BBB	1.230	35.427	61.064	3.187	39.736
Goodyear Tire & Rubr Co	B	7.671	65.509	88.106	2.245	39.840
H J Heinz Co	A	0.310	23.404	39.061	3.199	41.748
Hilton Hotels Corp	BBB	2.141	36.860	51.553	2.754	41.065
Home Depot Inc	AA	0.222	39.170	14.502	0.741	42.223

Table A1 (continued)

Company	Last Rating	Five Yr CDS (%)	Equity Volatility (%)	Leverage Ratio (%)	Asset Payout (%)	Recovery Rate (%)
IKON Office Solutions Inc	BB	3.460	48.604	73.673	1.337	38.221
Intl Business Machs Corp	A	0.381	31.166	32.683	0.578	39.991
Intl Paper Co	BBB	0.740	30.566	58.274	2.944	39.674
J C Penney Co Inc	BB	2.949	45.576	61.984	2.343	37.818
Jones Apparel Gp Inc	BBB	0.634	32.547	26.906	1.353	41.338
Kerr Mcgee Corp	BBB	0.745	26.472	59.613	3.398	41.242
Lockheed Martin Corp	BBB	0.501	32.241	44.982	1.815	41.173
Lowes Cos Inc	A	0.356	36.642	19.222	0.587	41.788
Ltd Brands Inc	BBB	0.584	44.878	21.283	3.854	41.529
Lucent Tech Inc	B	9.525	96.827	63.895	1.255	37.988
MGM MIRAGE	BB	2.167	33.197	57.910	2.675	39.764
Masco Corp	BBB	0.612	33.101	35.400	2.758	42.234
Mattel Inc	BBB	0.534	35.721	21.203	2.269	40.322
May Dept Stores Co	BBB	0.608	36.953	52.074	3.923	41.765
Maytag Corp	BBB	0.773	38.307	58.938	2.213	41.476
McDonalds Corp	A	0.322	38.651	30.956	2.107	40.051
Nordstrom Inc	BBB	0.609	40.304	43.145	1.555	41.820
Norfolk Sthn Corp	BBB	0.471	36.021	61.054	2.704	39.724
Northrop Grumman Corp	BBB	0.675	26.992	51.679	1.844	40.890
Omnicom Gp Inc	BBB	0.906	36.220	42.475	0.887	40.262
PPG Inds Inc	A	0.360	27.727	37.415	2.667	42.133
Phelps Dodge Corp	BBB	1.780	38.034	48.840	1.877	41.547
Pitney Bowes Inc	A	0.211	27.063	46.124	2.645	41.674
Praxair Inc	A	0.291	28.048	33.167	1.730	42.060
Procter & Gamble Co	AA	0.163	23.275	21.002	1.289	40.450
Rohm & Haas Co	BBB	0.353	29.283	43.281	2.241	42.235
Ryder Sys Inc	BBB	0.590	29.285	65.616	2.294	39.827
SBC Comms Inc	A	0.598	43.723	42.509	3.587	38.423
Safeway Inc	BBB	0.724	39.373	52.084	1.893	41.592
Sara Lee Corp	A	0.281	28.465	42.474	2.900	39.904
Sealed Air Corp US	BBB	2.349	35.792	44.043	1.820	37.390
Sherwin Williams Co	A	0.396	29.004	32.345	1.896	41.694
Solectron Corp	B	4.976	86.414	54.483	1.908	39.241
Southwest Airls Co	A	0.723	43.900	29.447	0.624	40.323
The Gap Inc	BB	2.889	50.769	27.086	1.429	41.034
The Kroger Co.	BBB	0.754	39.574	55.452	1.960	41.729
Tribune Co	A	0.413	25.200	34.934	1.500	41.228
Utd Tech Corp	A	0.260	30.856	37.047	1.116	39.475
V F Corp	A	0.323	25.458	31.046	2.687	38.877
Valero Engy Corp	BBB	1.075	36.741	65.574	2.174	40.715
Visteon Corp	BB	2.671	46.160	87.957	1.297	41.348
Wal Mart Stores Inc	AA	0.193	32.359	20.540	0.991	39.991
Walt Disney Co	BBB	0.714	43.767	38.906	1.644	39.191
Weyerhaeuser Co	BBB	0.753	29.759	62.255	3.509	41.164
Whirlpool Corp	BBB	0.477	31.043	58.506	2.305	40.512
Williams Cos Inc	B	6.836	84.181	83.953	3.724	35.851

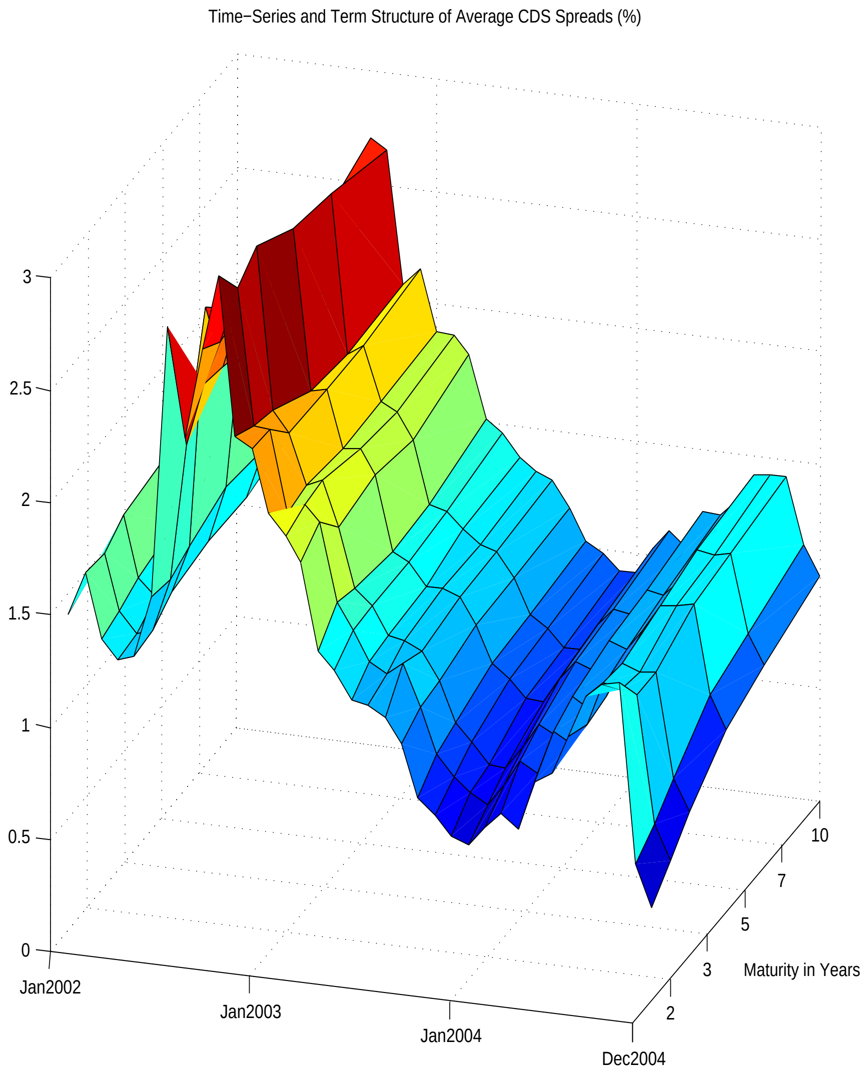
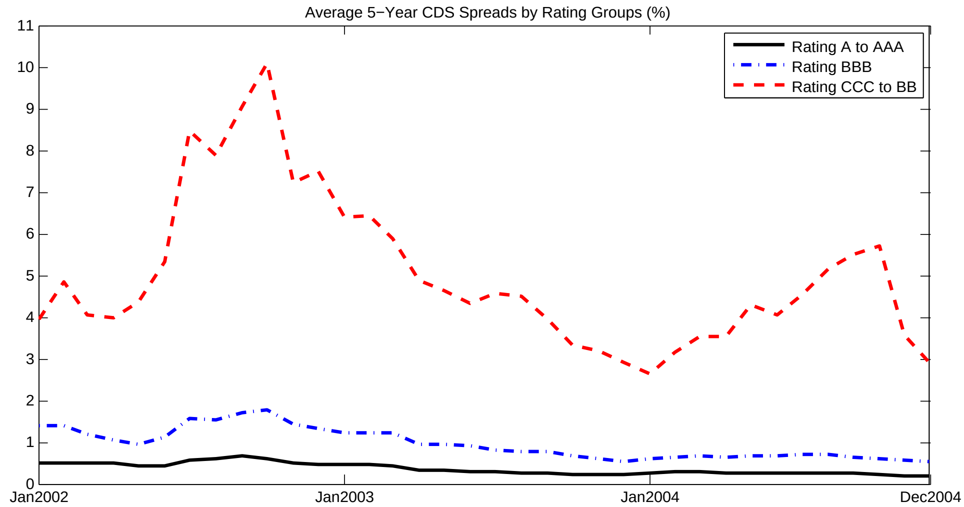


Fig. 1: Average CDS Spreads over the Full Sample Period

This figure plots the average CDS spreads of 93 firms with maturities ranging from 1 year to 10 years from January 2002 to December 2004. CDS spreads are in annualized percentage.



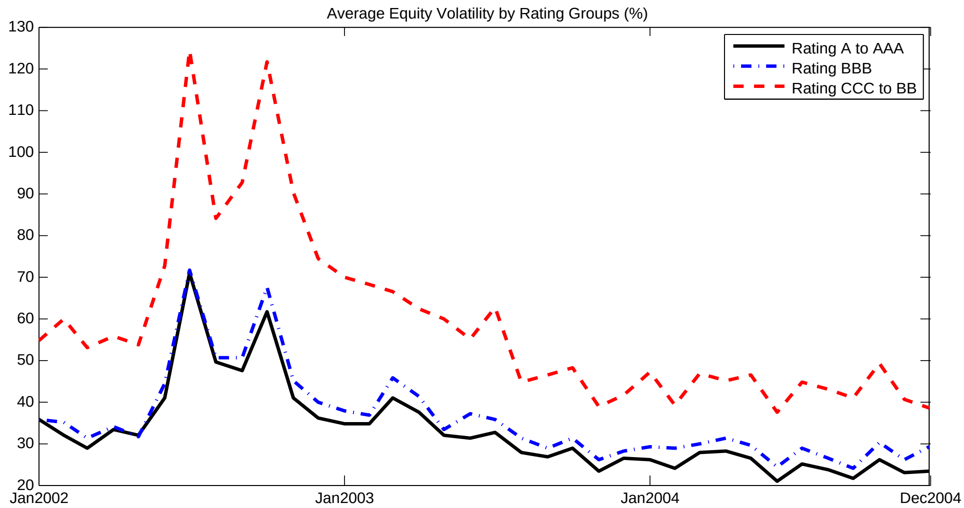


Fig. 2: Time Series of CDS Spreads and Equity Volatility

This figure plots the average 5-year CDS spread (top panel) and the average realized equity volatility (bottom panel) by rating groups (A-AAA, BBB, and CCC-BB) over the period January 2002–December 2004. Realized equity volatility is estimated using 5-minute intraday stock return data.

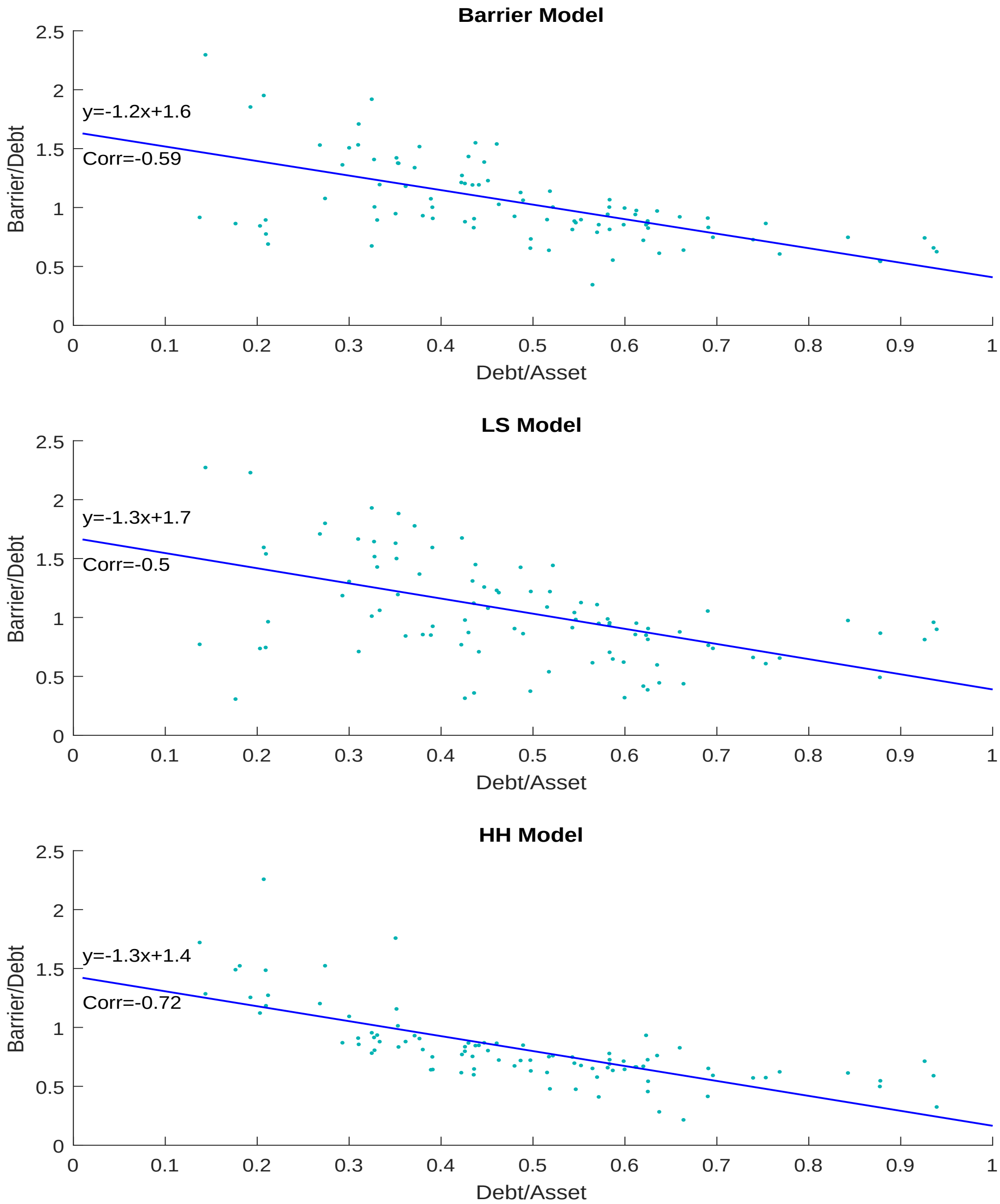


Fig. 3: Leverage Ratio and the Estimated Default Boundary

This figure shows three scatter plots between the observed leverage (debt/asset) ratio and the estimated default boundary (scaled by debt) for the sample of 93 firms over the period January 2002–December 2004. The three models with a flat barrier considered include Black and Cox (1976), Longstaff and Schwartz (1995), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002).

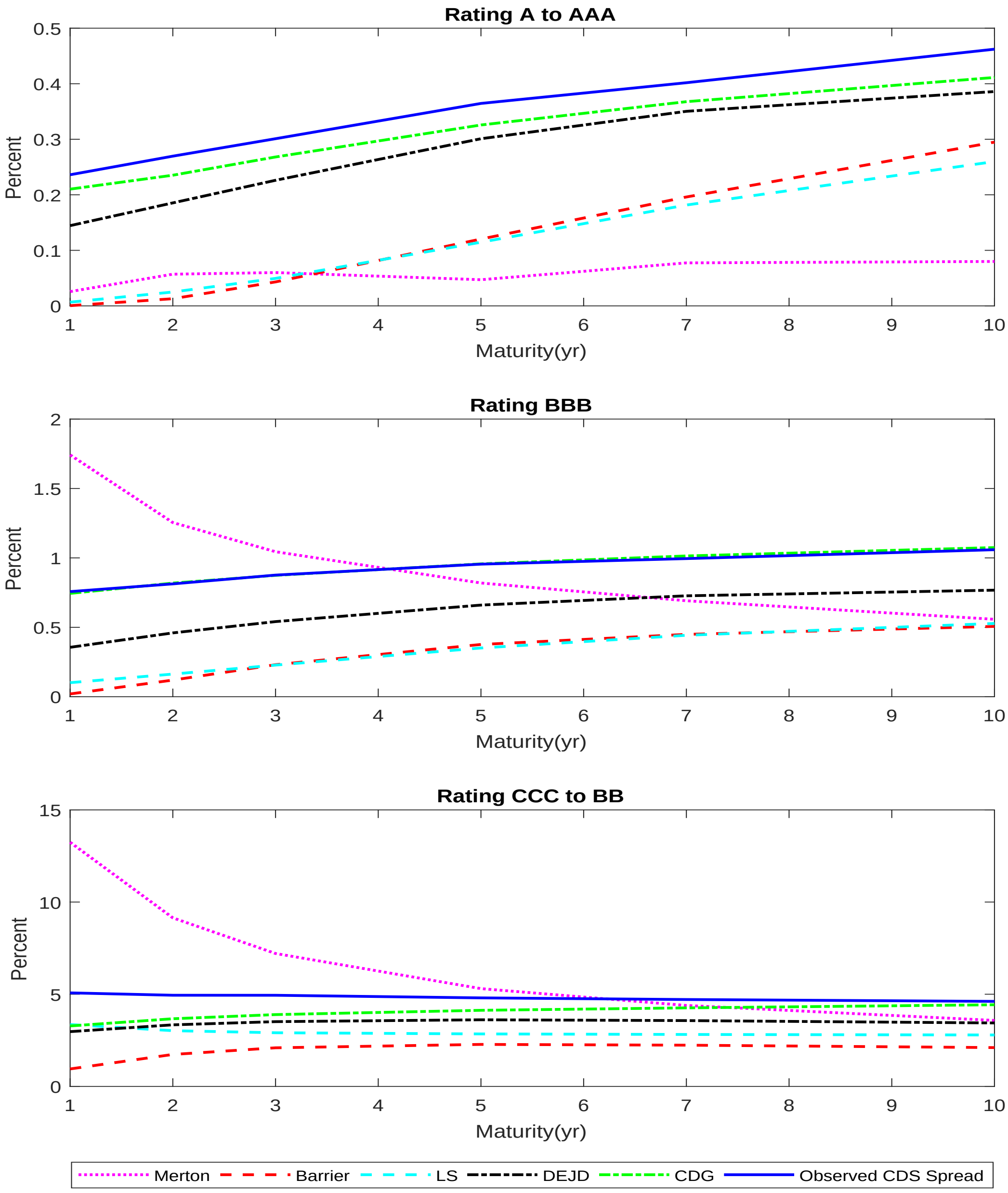


Fig. 4: Observed and Model-Implied CDS Term Structures

This figure plots the time-series average of both observed and model-implied CDS term structures, by three rating groups, over the period January 2002–December 2004. The structural models considered include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002).

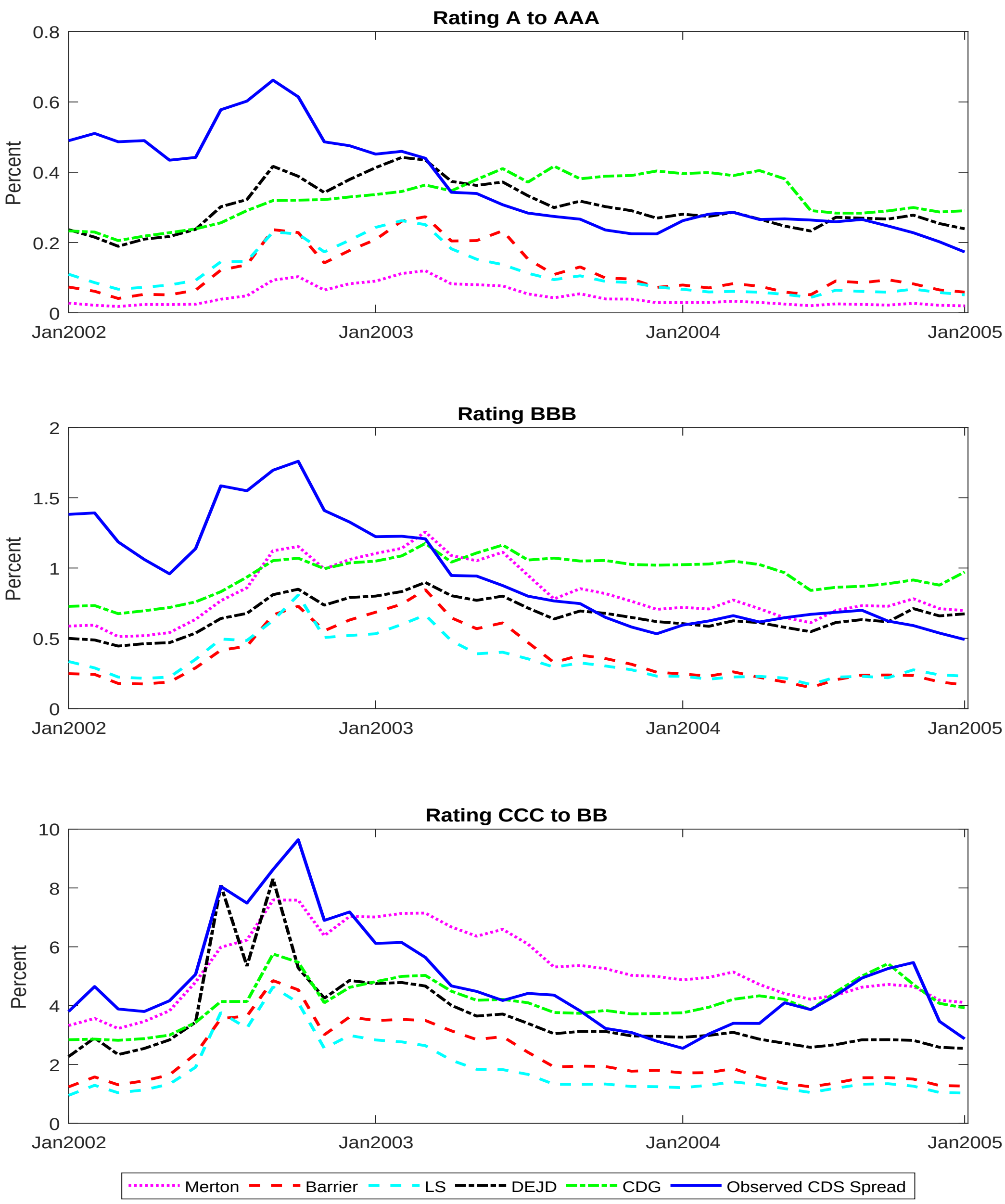


Fig. 5: Observed and Model-Implied 5-Year CDS Spreads

This figure plots observed and model-implied 5-year CDS spreads, for three rating groups, over the period January 2002–December 2004. The structural models considered include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002).

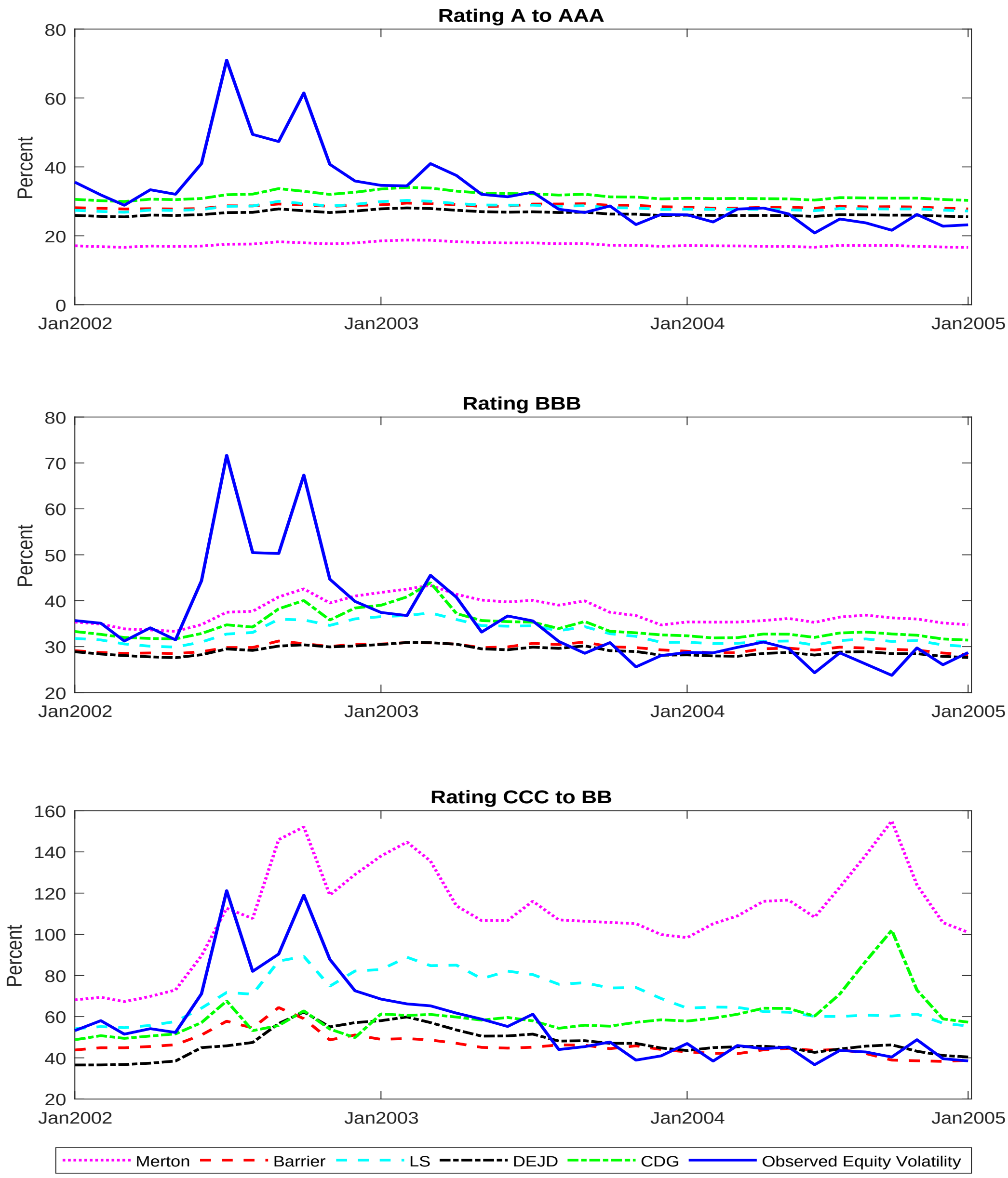


Fig. 6: Observed and Model Implied Equity Volatility

This figure plots the realized volatility—estimated using 5-minute intraday stock returns—and model-implied equity volatility, for three rating groups, over the period January 2002–December 2004. The structural models considered include Merton (1974), Black and Cox (1976), Longstaff and Schwartz (1995), Collin-Dufresne and Goldstein (2001), and the double exponential jump diffusion (DEJD) model used in Huang and Huang (2002).

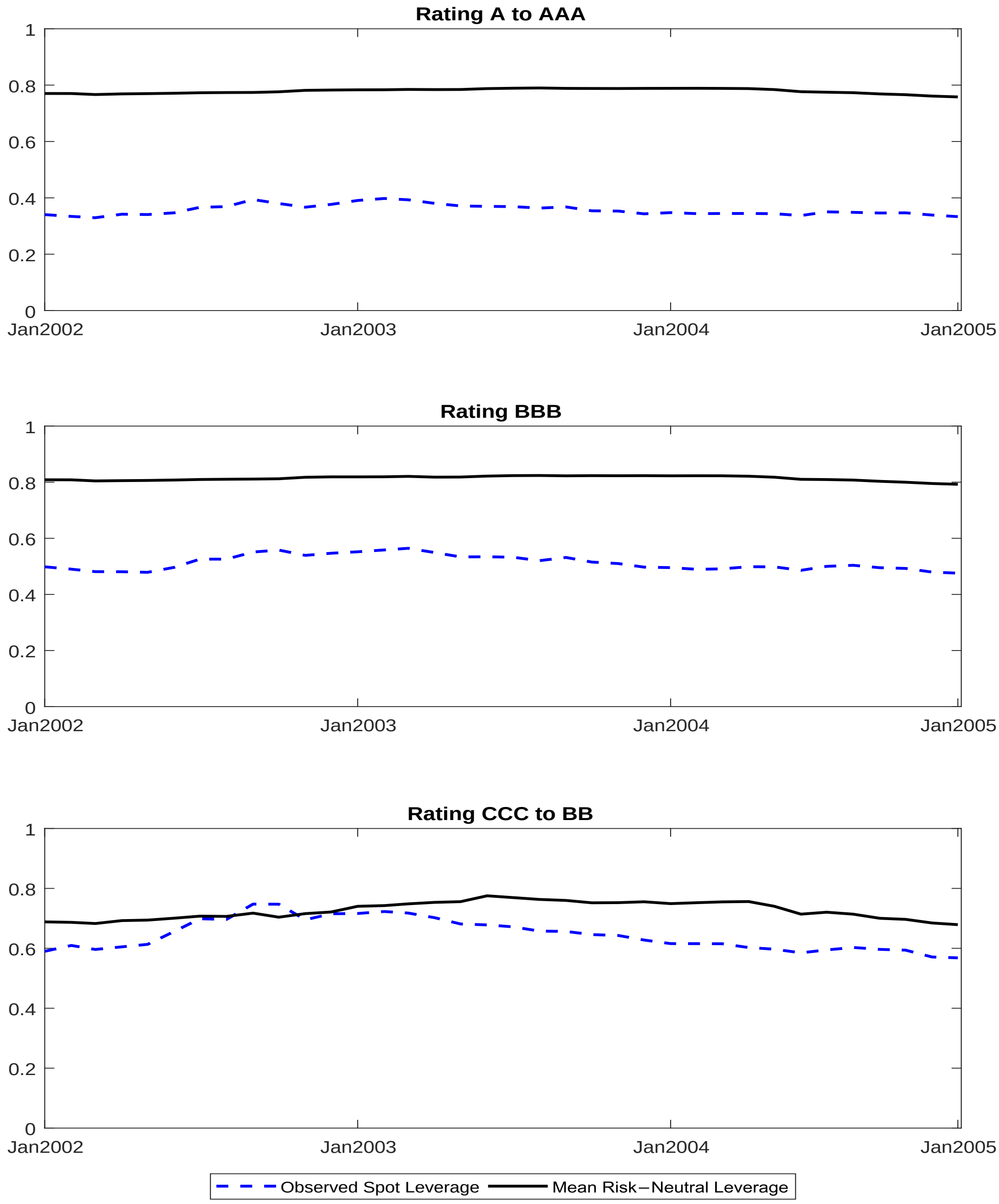


Fig. 7: Observed Spot Leverage and the Long-Run Mean of Risk-Neutral Leverage

This figure plots the observed spot leverage (debt/asset) and the model-implied long-run mean of the risk-neutral leverage, for three rating groups, over the period January 2002–December 2004. The long-run mean of the risk-neutral leverage is estimated using the Collin-Dufresne and Goldstein (2001) model.

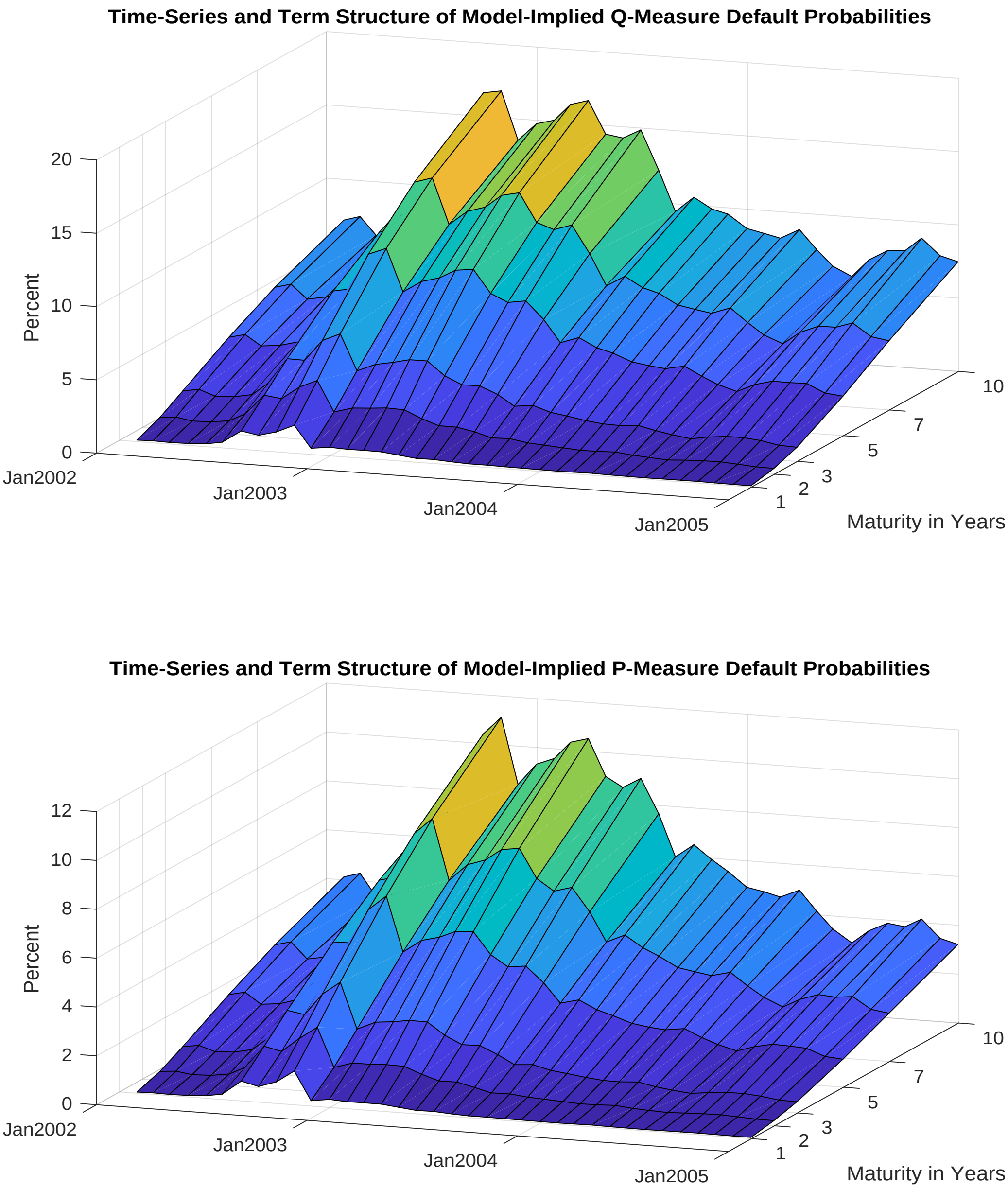


Fig. 8: Model Implied Risk-Neutral and Real Default Probabilities

This figure plots the time series and term structure of model-implied default probabilities under either the risk-neutral measure (panel A) or the physical measure (panel B) based on the Black and Cox (1976) model.

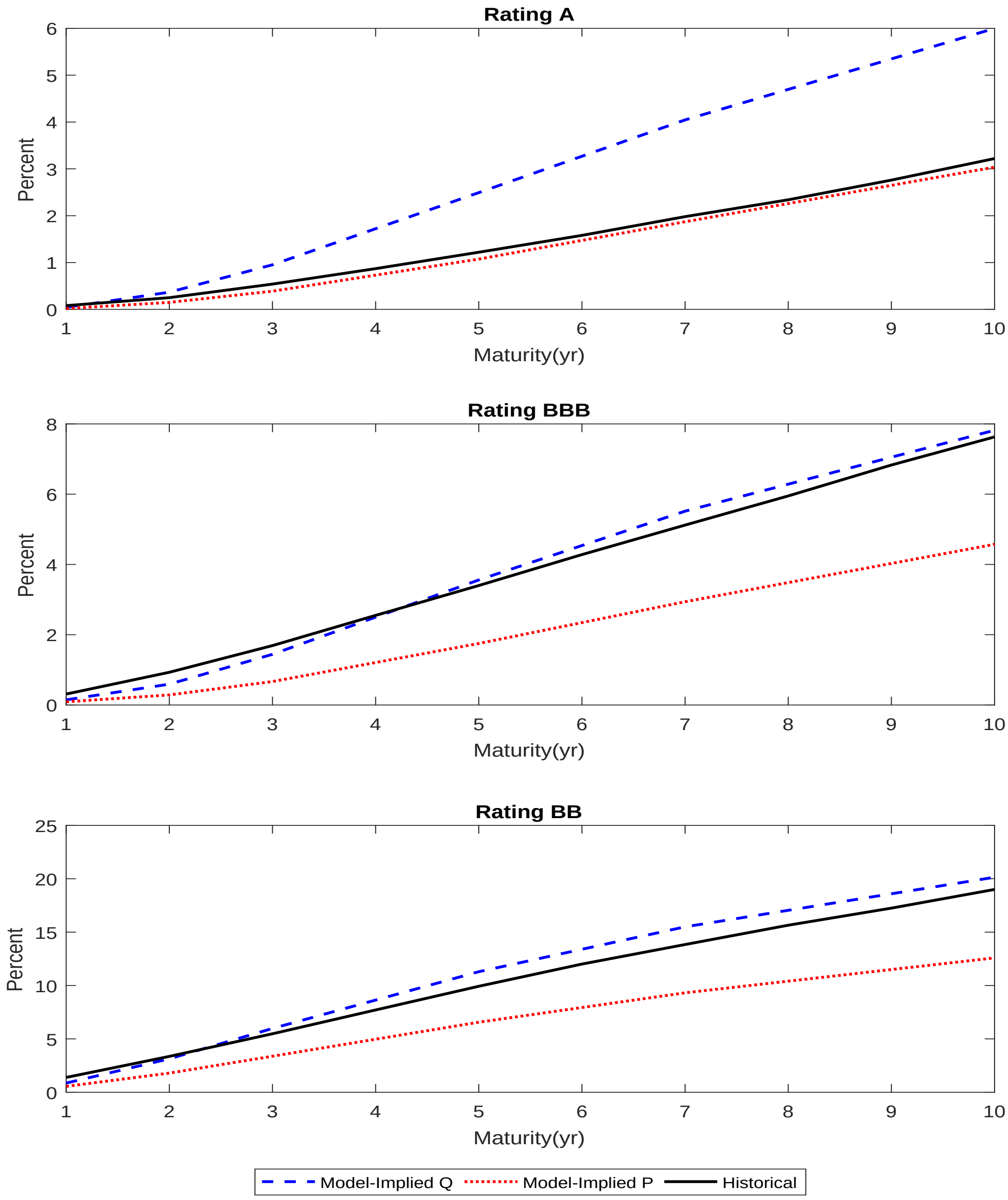


Fig. 9: Term Structures of Average Default Rates, and Model Implied Risk-Neutral and Real Default Probabilities

This figure plots the term structure of average default rates (solid line), model-implied default probabilities under both the risk-neutral measure (blue dashed line) and the physical measure (red dotted line) based on the Black and Cox (1976) model, for three different rating groups, single A (panel A), BBB (panel B), and BB (panel C).

References

Acharya, V. and Carpenter, J. (2002) Corporate bond valuation and hedging with stochastic interest rates and endogenous bankruptcy, *Review of Financial Studies* **15**, 1355–1383.

Acharya, V., Huang, J.-Z., Subrahmanyam, M., and Sundaram, R. K. (2006) When does strategic debt-service matter? *Economic Theory* **29**(2), 363–378.

Acharya, V., Huang, J.-Z., Subrahmanyam, M., and Sundaram, R. K. (2019) Costly financing, optimal payout policies and the valuation of corporate debt, In M. Crouhy, D. Galai, and Z. Wiener (Eds.), *Contingent Claims Analysis in Corporate Finance*, Volume 3. Singapore: World Scientific.

Andersen, T. G., Bollerslev, T., Diebold, F. X., and Labys, P. (2001) The distribution of realized exchange rate volatility, *Journal of the American Statistical Association* **96**, 42–55.

Anderson, R. W. and Sundaresan, S. (1996) Design and valuation of debt contracts, *Review of Financial Studies* **9**(1), 37–68.

Arora, N., Bohn, J., and Zhu, F. (2005) Reduced form vs. structural models of credit risk: A case study of three models, *Journal of Investment Management* **3**(4), 43–67.

Bai, J., Goldstein, R., and Yang, F. (2018) Is the credit spread puzzle a myth?, *Working Paper*, Georgetown University, University of Minnesota, and University of Connecticut.

Bai, J. and Wu, L. (2016) Anchoring credit default swap spreads to firm fundamentals, *Journal of Financial and Quantitative Analysis* **51**(5), 1521–1543.

Bao, J. (2009) Structural models of default and the cross section of corporate bond yield spreads, *working paper*, MIT.

Bao, J., Chen, J., Hou, K., and Lu, L. (2015) Prices and volatilities in the corporate bond market, *American Finance Association 2015 Boston Meetings Paper*, available at http://dx.doi.org/10.2139/ssrn.2651243.

Bao, J. and Hou, K. (2017) De facto seniority, credit risk, and corporate bond prices, *The Review of Financial Studies* **30**(11), 4038–4080.

Bao, J. and Pan, J. (2013) Bond illiquidity and excess volatility, *Review of Financial Studies* **26**(12), 3068–3103.

Bao, J., Pan, J., and Wang, J. (2011) Liquidity of corporate bonds, *Journal of Finance* **66**, 911–946.

Barndorff-Nielsen, O. and Shephard, N. (2002) Estimating quadratic variation using realized variance, *Journal of Applied Econometrics* **17**, 457–478.

Barndorff-Nielsen, O. and Shephard, N. (2004) Power and bipower variation with stochastic volatility and jumps, *Journal of Financial Econometrics* **2**, 1–48.

Bertsimas, D., Kogan, L., and Lo, A. W. (2000) When is time continuous? *Journal of Financial Economics* **55**(2), 173–204.

Black, F. and Cox, J. (1976) Valuing corporate securities: Some effects of bond indenture provisions, *Journal of Finance* **31**, 351–367.

Black, F. and Scholes, M. (1973) The pricing of options and corporate liabilities, *Journal of Political Economy* **81**(3), 637–654.

Bollerslev, T., Chou, R., and Kroner, K. (1992) ARCH modeling in finance: A review of the theory and empirical evidence, *Journal of Econometrics* **52**(1), 5–59.

Bollerslev, T., Engle, R., and Nelson, D. (1994) ARCH models, In R. Engle and D. McFadden (Eds.), *Handbook of Econometrics*, Volume 4. Amsterdam: Elsevier Science B.V.

Bongaerts, D., de Jong, F., and Driessen, J. (2017) An asset pricing approach to liquidity effects in corporate bond markets, *Review of Financial Studies* **30**(4), 1229–1269.

Campbell, J. and Taksler, G. (2003) Equity volatility and corporate bond yields, *Journal of Finance* **58**, 2321–2349.
Chen, L., Collin-Dufresne, P., and Goldstein, R. S. (2008) On the relation between the credit spread puzzle and the equity premium puzzle, *Review of Financial Studies* **22**(9), 3367–3409.
Chen, L., Lesmond, D. A., and Wei, J. (2007) Corporate yield spreads and bond liquidity, *Journal of Finance* **62**(1), 119–149.
Chen, L. and Zhao, X. (2006) Why do more profitable firms have lower leverage ratios? *working paper*.
Chen, N. and Kou, S. G. (2009) Credit spreads, optimal capital structure, and implied volatility with endogenous default and jump risk, *Mathematical Finance* **19**(3), 343–378.
Chen, R., Fabozzi, F., Pan, G., and Sverdlove, R. (2006) Sources of credit risk: Evidence from credit default swaps, *Journal of Fixed Income* **16**(3), 7–21.
Cochrane, J. H. (2009) *Asset Pricing: Revised edition.* Princeton university press.
Collin-Dufresne, P. and Goldstein, R. (2001) Do credit spreads reflect stationary leverage ratios?, *Journal of Finance* **56**, 1929–1957.
Collin-Dufresne, P., Goldstein, R., and Martin, S. (2001) The determinants of credit spread changes, *Journal of Finance* **56**, 2177–2207.
Cremers, M., Driessen, J., and Maenhout, P. (2008) Explaining the level of credit spreads: Option-implied jump risk premia in a firm value model, *Review of Financial Studies* **21**(5), 2209–2242.
Das, S. and Hanouna, P. (2009) Hedging credit: Equity liquidity matters, *Journal of Financial Intermediation* **18**(1), 112–123.
Dick-Nielsen, J., Feldhütter, P., and Lando, D. (2012) Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics* **103**, 471–492.
Du, D., Elkamhi, R., and Ericsson, J. (2018) Time-varying asset volatility and the credit spread puzzle, *Journal of Finance*, forthcoming.
Duan, J. (1994) Maximum likelihood estimation using price data of the derivative contract, *Mathematical Finance* **4**(2), 155–167.
Duffie, D. and Lando, D. (2001) Term structures of credit spreads with incomplete accounting information, *Econometrica* **69**(3), 633–664.
Eom, Y. H., Helwege, J., and Huang, J.-Z. (2004) Structural models of corporate bond pricing: An empirical analysis, *Review of Financial Studies* **17**, 499–544.
Ericsson, J., Jacobs, K., and Oviedo, R. (2009) The determinants of credit default swap premia, *Journal of Financial and Quantitative Analysis* **44**(1), 109–132.
Ericsson, J. and Reneby, J. (2005) Estimating structural bond pricing models, *Journal of Business* **78**(2), 707–735.
Feldhütter, P. and Schaefer, S. (2018) The myth of the credit spread puzzle, *Review of Financial Studies*, forthcoming.
Ferson, W. E. and Foerster, S. R. (1994) Finite sample properties of the generalized method of moments in tests of conditional asset pricing models, *Journal of Financial Economics* **36**(1), 29–55.
François, P. and Morellec, E. (2004) Capital structure and asset prices: Some effects of bankruptcy procedures, *Journal of Business* **77**(2), 387–411.
Frank, M. and Goyal, V. (2003) Testing the pecking order theory of capital structure, *Journal of Financial Economics* **67**(2), 217–248.
Friewald, N., Jankowitsch, R., and Subrahmanyam, M. (2012) Illiquidity or credit deterioration: A study of liquidity in the U.S. corporate bond market during financial crises,

Journal of Financial Economics **105**, 18–36.
Geske, R. (1977) The valuation of corporate liabilities as compound options, *Journal of Financial and Quantitative Analysis* **12**(4), 541–552.
Hall, A. R. (2005) *Generalized method of moments.* Oxford university press.
Han, S. and Zhou, H. (2016) Effects of liquidity on the non-default component of corporate yield spreads: Evidence from intraday transactions data, *Quarterly Journal of Finance* **6**(03), 1650012 (49 pages).
Hansen, L. P. (1982) Large sample properties of generalized method of moments estimators, *Econometrica* **50**(4), 1029–1054.
Hansen, L. P., Heaton, J., and Yaron, A. (1996) Finite-sample properties of some alternative gmm estimators, *Journal of Business & Economic Statistics* **14**(3), 262–280.
Hansen, L. P. and Singleton, K. J. (1982) Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica*, 1269–1286.
He, Z. and Milbradt, K. (2014) Endogenous liquidity and defaultable bonds, *Econometrica* **82**(4), 1443–1508.
He, Z. and Xiong, W. (2012) Rollover risk and credit risk, *Journal of Finance* **67**(2), 391–430.
Helwege, J., Huang, J.-Z., and Wang, Y. (2014) Liquidity effects in corporate bond spreads, *Journal of Banking & Finance* **45**, 105–116.
Huang, J.-Z. (2005) Affine structural models of corporate bond pricing, *working paper*, Penn State University.
Huang, J.-Z. and Huang, M. (2002) How much of the corporate-treasury yield spread is due to credit risk? *NBER Asset Pricing Fall 2002 Conference Paper*, Available at http://ssrn.com/abstract=1295816.
Huang, J.-Z. and Huang, M. (2012) How much of the corporate-treasury yield spread is due to credit risk?, *Review of Asset Pricing Studies* **2**, 153–202.
Huang, J.-Z., Rossi, M., and Wang, Y. (2015) Sentiment and corporate bond valuations before and after the onset of the credit crisis, *Journal of Fixed Income* **25**, 34–57.
Huang, J.-Z. and Shi, Z. (2016) Hedging interest rate risk using a structural model of credit risk, *working paper*, Penn State University.
Hull, J., Nelken, I., and White, A. (2004) Merton's model, credit risk, and volatility skews, *Journal of Credit Risk* **1**(1), 3–27.
Jagannathan, R., Skoulakis, G., and Wang, Z. (2002) Generalized methods of moments: Applications in finance, *Journal of Business & Economic Statistics* **20**(4), 470–481.
Jones, E. P., Mason, S. P., and Rosenfeld, E. (1984) Contingent claims analysis of corporate capital structures: An empirical investigation, *Journal of Finance* **39**, 611–625.
Kapadia, N. and Pu, X. (2012) Limited arbitrage between equity and credit markets, *Journal of Financial Economics* **105**(3), 542–564.
Kelly, B. T., Manzo, G., and Palhares, D. (2016) Credit-implied volatility, *working paper*, Chicago Booth.
Kocherlakota, N. R. (1990) On tests of representative consumer asset pricing models, *Journal of Monetary Economics* **26**(2), 285–304.
Kou, S. G. (2002) A jump-diffusion model for option pricing, *Management science* **48**(8), 1086–1101.
Leland, H. E. (2004) Predictions of default probabilities in structural models of debt, *Journal of Investment Management* **2**(2), 5–20.
Leland, H. E. and Toft, K. B. (1996) Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads, *Journal of Finance* **51**, 987–1019.

Lettau, M. and Ludvigson, S. (2001) Resurrecting the (C) CAPM: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* **109**(6), 1238–1287.

Longstaff, F., Mithal, S., and Neis, E. (2005) Corporate yield spreads: Default risk or liquidity? New evidence from the credit-default-swap market, *Journal of Finance* **60**, 2213–2253.

Longstaff, F. and Schwartz, E. (1995) A simple approach to valuing risky fixed and floating rate debt, *Journal of Finance* **50**, 789–820.

Mahanti, S., Nashikkar, A., Subrahmanyam, M. G., Chacko, G., and Mallik, G. (2008) Latent liquidity: A new measure of liquidity, with an application to corporate bonds, *Journal of Financial Economics* **88**(2), 272–298.

McQuade, T. J. (2018) Stochastic volatility and asset pricing puzzles, *working paper*, Stanford University.

Meddahi, N. (2002) A theoretical comparison between integrated and realized volatility, *Journal of Applied Econometrics* **17**, 479–508.

Mella-Barral, P. and Perraudin, W. (1997) Strategic debt service, *Journal of Finance* **52**(2), 531–556.

Merton, R. (1974) On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* **29**, 449–470.

Merton, R. (1976) Option pricing when underlying stock returns are discontinuous, *Journal of Financial Economics* **3**(1), 125–144.

Newey, W. K. and West, K. D. (1987) A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* **55**, 703–708.

Perrakis, S. and Zhong, R. (2015) Credit spreads and state-dependent volatility: Theory and empirical evidence, *Journal of Banking & Finance* **55**, 215–231.

Predescu, M. (2005) The performance of structural models of default for firms with liquid cds spreads, *working paper*, Rotman School of Management, University of Toronto.

Ramezani, C. A. and Zeng, Y. (2007) Maximum likelihood estimation of the double exponential jump-diffusion process, *Annals of Finance* **3**(4), 487–507.

Schaefer, S. and Strebulaev, I. A. (2008) Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* **90**, 1–19.

Schestag, R., Schuster, P., and Uhrig-Homburg, M. (2016) Measuring liquidity in bond markets, *Review of Financial Studies* **29**(5), 1170–1219.

Shi, Z. (2019) Time-varying ambiguity, credit spreads, and the levered equity premium, *Journal of Financial Econommics*, forthcoming.

Strebulaev, I. A. and Yang, B. (2013) The mystery of zero-leverage firms, *Journal of Financial Economics* **109**(1), 1–23.

Sundaresan, S. (2013) A review of Merton's model of the firm's capital structure with its wide applications, *Annual Reviews of Financial Economics* **5**(1), 21–41.

Tauchen, G. (1986) Statistical properties of generalized method-of-moments estimators of structural parameters obtained from financial market data, *Journal of Business and Economic Statistics* **4**(4), 397–416.

Vasicek, O. A. (1977) An equilibrium characterization of the term structure, *Journal of Financial Economics* **5**, 177–188.

Zhang, B. Y., Zhou, H., and Zhu, H. (2009) Explaining credit default swap spreads with equity volatility and jump risks of individual firms, *Review of Financial Studies* **22**(12), 5099–5131.