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Default Dependence: The Equity Default Relationship

by

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Abstract

The paper examines three equity-based structural models to study the nonlinear relationship between equity and credit default swap (CDS) prices. These models differ in the specification of the default barrier. With cross-firm CDS premia and equity information, we are able to estimate and compare the three models. We find that the stochastic barrier model performs better than the constant and uncertain barrier models in terms of both in-sample fit and out-of-sample forecasting of CDS premia. In addition, we demonstrate a linkage between the default barrier, jump intensity, and barrier volatility estimated from our models and firm-specific variables related to default risk, such as credit ratings, equity volatility, and leverage ratios.

JEL classification: G12, G13
Bank classification: Econometric and statistical methods; Financial markets

Résumé

Les auteurs étudient la relation non linéaire entre les prix des actions et les primes de swaps sur défaillance dans le cadre de trois modèles structurels qui formalisent le processus d'évolution du prix des actions et qui se différencient par leur spécification du seuil de défaillance. Ils estiment et comparent ces modèles à partir de données relatives aux primes de swaps sur défaillance et aux prix des actions d'un éventail d'entreprises. Ils constatent que le modèle à seuil stochastique présente une meilleure adéquation statistique et permet de mieux prévoir les primes de swaps hors échantillon que les modèles à seuil constant et à seuil incertain. Les auteurs mettent aussi en évidence l'existence d'un lien entre, d'une part, le seuil de défaillance, l'intensité du saut et la volatilité du seuil estimés à l'aide de leurs modèles et, d'autre part, des variables indicatrices du risque de défaillance propre à l'entreprise telles que la cote de crédit de celle-ci, la volatilité du prix de ses actions et ses ratios de levier.

Classification JEL : G12, G13
Classification de la Banque : Méthodes économétriques et statistiques; Marchés financiers

1 Introduction

This paper directly examines the relationship between credit default swap (CDS) premia and equity prices in an equity-based credit model which incorporates elements of both structural and reduced form models. The equity price is a combination of a lognormal process and a jump process. Default time is defined as the first time the equity price either crosses a barrier or jumps to zero. Cross-sectional CDS and equity data are used to estimate and compare models with different specifications of the default barrier. We demonstrate a linkage between default barrier, jump intensity, and barrier volatility estimated from our models and firm-specific variables, such as credit ratings, equity volatility, and leverage ratios, that are related to default risk.

In the credit risk literature, default risk is closely related to equity risk. The structural models, pioneered by Black and Sholes (1973) and Merton (1974), take as given the dynamics of the asset value of the issuing company, and price debt and equity as contingent claims on the asset. Numerous empirical studies (Jones, Mason, and Rosenfeld (1984), Elton, Gruber, Agrawal, and Mann (2001), Huang and Huang (2003) and Eom, Helwege and Huang (2004)) use equity data to calibrate those models and then predict corporate-Treasury yield spreads. The results suggest that credit risk is only one of the factors contributing towards the corporate-Treasury yield spread. Other factors, such as illiquidity and asymmetric tax treatment of Treasury and corporate bonds, are also important to explain the corporate-Treasury yield spread. Recently, with the rapid growth of credit derivative markets, researchers began to use credit default swaps (CDS) to study default risk since they are less susceptible to liquidity risk (Longstaff, Mithal, and Neis (2005)). A number of studies have studied the relationship between CDS and equity in a regression framework (Ericsson, Jacobs and Oviedo (2005), Zhang, Zhou, and Zhu (2005), and Cao, Zhong and Yu (2007)). However, the relationship between CDS and equity is nonlinear as predicted by the structural models. Although these studies show the importance of some firm characteristics, such as equity volatility, implied volatility and equity jump intensity, in predicting CDS spreads, they are less useful if one wants to examine the performance of using CDS to hedge against equity risk.

In the Merton (1974) model, default can occur only at the maturity of debt, and the value of equity is zero upon default. However, it is empirically observed that the value of the equity is still positive though very small after a default because of the violation of the absolute priority rule. In addition, default can occur at any point in time, implying that the Merton model is not directly applicable. An alternative approach to circumvent this limitation is to assume that if the firm's value falls below some critical value (a barrier), default occurs. For this approach to be operational, it is necessary to specify the critical value. However, these barrier models are difficult to calibrate to real world data and accuracy is a serious problem (Huang and Huang (2003) and Eom, Helwege and Huang (2004)). These difficulties have lead to a number of different approaches. CreditGrades (2002) starts with the usual assumption that the market value of a firm's assets follows a lognormal process. If the firm's value falls below a critical value threshold, default is assumed to occur. The critical value is modeled as a random variable. After a series of approximations and simplifying assumptions, the model directly links equity price, equity volatility, and the credit default swap price. Instead of modeling the value of the firm and then being forced into making a long list of simplifying assumptions, Trinh (2004) starts with the equity price as a primitive. The equity price is assumed to follow a diffusion plus jump process. If the equity price falls below a critical price, default is assumed to occur. The critical value is modeled as a lognormal process. Trinh (2004) only demonstrates the ability of the model to generate different shapes of CDS curves, and does not use actual data to test the model.

We extend the CreditGrades (2002) and Trinh (2004) approaches to estimate equity-based models developed under the assumption of no-arbitrage opportunities. So we can directly examine the nonlinear relationship between CDS premia and equity prices. In addition, we compare models with different specifications of the default barrier. We demonstrate a linkage between the default barrier and firm-specific characteristics related to default risk. We first test two formulations of a simple barrier model. This is a variant of the model first described in CreditGrades (2002). In the first case, the barrier is represented as a constant (the constant barrier model) and, in the second case, as an unobservable random variable (the uncertain barrier model). The dynamics of the stock price are described by a diffusion plus jump. If a jump occurs, this signals default and the resulting value of equity is assumed to be zero. If no jump occurs, default will occur the first time that equity crosses a barrier. In this case equity is assumed to have some positive value post default, implying that the recovery rates will depend on the nature of the process driving default. We then assume that the barrier is described by a lognormal stochastic process (the stochastic barrier model), as in Trinh (2004).

Using a large number of cross-sectional CDS and equity data, we estimate and compare the three models. We find that the stochastic barrier model performs the best in both in-sample fitting and out-of-sample forecasting the CDS premia. In addition, we investigate the relationship between estimated default barriers, jump intensities, and barrier volatilities and variables such as credit ratings, equity volatilities, and accounting variables, which have been used in the literature to explain cross-firm variations of default risk. We find that, in general the estimated default barrier to equity price ratio is higher for firms with low credit ratings. It is positively related to the leverage ratios when we control for credit ratings and equity volatility. The estimated jump intensity is also higher for firms with low credit ratings. It is positively related to equity volatility. These findings are consistent across the three models. Within each credit class, the estimated barrier volatility from the stochastic barrier and uncertain barrier models is in general positively related to equity volatility. The results demonstrate that there is a close relationship between equity and CDS prices.

A literature review is given in Section 2. We first describe existing empirical work relating equity and credit default prices. In Section 3 we describe the models that we will test. Data and empirical methodologies for the study are given in Section 4. Estimation results are presented in Section 5. Section 6 concludes.

2 Literature Review

In the Merton (1974) model, the value of the firm is assumed to follow a lognormal process as described by

$$\frac{dV}{V} = (\mu - \delta)dt + \sigma dW \tag{1}$$

where μ is the instantaneous expected ex dividend rate of return; δ is the dividend yield; σ is the volatility of the firm; and $W(t)$ is a Brownian motion. If $V(0)$ denotes the current value of the firm, then

$$V(t) = V(0)\exp[(\mu - \delta - \sigma^2/2)t + \sigma W(t)] \tag{2}$$

where $V(t)$ denotes the value of the firm at time t. In the Merton model, default can only occur when the firm's zero coupon debt matures. In a barrier model, default will occur the first time the firm's value falls below the barrier. The time to default τ, is described by

$$\tau = \inf\{t; V(t) \leq B_t | V(0) > B_0\} \tag{3}$$

where B_t is the level of the barrier at time t. In Black and Cox (1976), the barrier is assumed to be an exponential function of time, while in Longstaff and Schwartz (1995) the barrier is a constant. In both cases, it is possible to derive closed form expressions for the probability of survival. Zhou (2001) extends this framework by adding a jump to the process for the value of the firm

$$\frac{dV}{V} = (\mu - \delta + \lambda)dt + \sigma dW + (\Pi - 1)dN \tag{4}$$

where Π is the jump magnitude; dN is a Poisson process with intensity λ. It is assumed that the size of the jumps are described by a lognormal process. Zhou (2001) describes an algorithm to derive the survival time.

2.1 Empirical Evidence

In the application of structural models, two different approaches have been used for calibration, and each of which reaches quite different conclusions. In the first approach, the models are calibrated to the term structure of default probabilities under the natural probability measure, while the second approach uses firm value, leverage, payout ratio and estimates the exogenous parameters, such as the default interest rate process.

For the first approach, Huang and Huang (2003) calibrate a wide array of structural models, including jump-diffusion models, and generate a term structure of credit spreads for different credit categories. The models are calibrated to match (1) the average probability of default under the natural probability measure over different horizons; (2) the average loss as a fraction of the face value of debt; (3) the average leverage ratio; and (4) the equity premium. They find that for investment grade firms these models can explain less than 30 percent of the average credit spread. For firms below investment grades, the models can explain between 60 to 80 percent of the average credit spread.

Using the second approach, Eom, Helwege and Huang (2004) test five different structural models. They use firm specific parameters such as firm value, leverage, payout ratio etc., based on historical corporate data. They find that the Merton (1994) model generates spreads that are too small. The Leland and Toft (1996) model over-estimates spreads, even for short maturity bonds. The Longstaff and Schwartz (1995) model also generates spreads that are too high on average. The model generates excessive spreads for risky bonds and under-estimates the spreads for low risk bonds. The Collin-Dufresne and Goldstein (2001) model over-estimates spreads on average. Eom, Helwege and Huang conclude that structural models do not systematically under-predict credit spreads, but accuracy is a major problem.

Longstaff, Mithal and Neis (2005) use corporate bond yield data to infer the implied probabilities of default. These implied probabilities of default are used to determine credit default swap premiums. It is found that the implied premiums are higher than the market premiums. It is also found that equity and credit default swap markets tend to lead corporate bond markets. Blanco, Brennan and Marsh (2005) and Zhu (2004) reach a similar conclusion. Blanco, Brennan and Marsh (2005) also examine the determinants of changes in credit default swap premiums. Changes in the ten-year Treasury yield, the slope of the yield curve, firm specific equity returns and volatility are found to be statistically significant explanatory variables. Ericsson, Jacobs and Oviedo (2004) regress (*a*) the premium and (*b*) the premium difference against leverage[1], equity volatility and the 10-year Treasury yield. All coefficients were statistically significant. Zhang, Zhou and Zhu (2005) examine the determinants of the credit default premium. They find that firm specific variables, such as recovery rate, return on equity, leverage and firm credit rating and the macro variables, such as Standard & Poor's 500 index and volatility, the three-month Treasury yield and term spread, to be statistically significant. They also demonstrate that credit default swap premiums depend on including jumps into the specification of the pricing dynamics for equity.

If structural or reduced form approaches are used to model credit default swap premiums, there is a non-linear relationship between the underlying state variables and premiums. However, all of the above studies examining the determinants of credit default premiums assume a linear relation between state variables and premiums, implying a mis-specification[2].

3 Model Description

A structural model is needed to study the nonlinear relationship between equity and default risk measured from either debt or CDS data. Most structural models start with a dynamic process of the firm value, and price equity and debt as contingent claims on the firm value. In addition, information on the capital structure of a firm is needed in

[1] This is defined as book value of debt divided by market value of equity plus the book value of debt plus preferred shares

[2] In a survey by Meng and Gwilym (2004), all the empirical studies assume a linear relation.

those models. However, it is difficult to observe the capital structure of a firm because the accounting information reported by a firm is often noisy. Furthermore, the firm value is usually not observable, and is inferred from equity value. Its validity depends on the chosen structural model.

To side-step many of the calibration problems that arise when the value of the firm is used as a primitive variable, Trinh (2004) takes the equity process as a primitive state variable. A similar logic is employed in the Black-Scholes options pricing model, where the stochastic process describing changes in equity price is taken as exogenous, even though equity is a call option on the value of the firm's assets. We first describe Trinh's (2004) approach since we use the same methodology.

The stochastic process describing the stock price in Trinh (2004) is given by

$$\frac{dS}{S} = (r - \delta + \lambda)dt + \sigma_S dW_s - dN \tag{5}$$

where N_t is a jump process that equals zero before the jump and one after a jump. The intensity is denoted by λ. Note that, unlike expression (4), there is only one jump. When a jump occurs, the value of equity goes to zero. In other words, if a jump occurs, the firm defaults. The assumption of a surprise jump to default is clearly restrictive, the trade-off being that it is possible to derive relatively simple expressions for the survival time. The barrier is described by a lognormal stochastic process of the form

$$\frac{dB}{B} = \mu_B dt + \sigma_B dW_B \tag{6}$$

where the barrier drift parameter μ_B and volatility σ_B are assumed to be constant. The Brownian motions W_S and W_B are assumed to be independent.

In this framework there are two stopping times. The first time is for default when there is no jump. Default is not a surprise, since the stock price slowly drifts towards the barrier. In the second case the stock is above the barrier and a jump occurs. The time to default is defined as the minimum of the stopping times. For the firm to survive until time t depends on the events of (a) the barrier not being crossed and (b) no jump.

Trinh (2004) derives expressions for the probability of survival, the values of European call and put options, and spread curves. In this framework, the following variables are taken as exogenous: the LIBOR term structure, either credit default swap or bond prices, the time to maturity for the swap or bond, the recovery rate, and the current stock price.

It is necessary to infer the stock volatility, the intensity of the jump, and the parameters describing the evolution of the barrier. Trinh (2004) only demonstrates that the model can generate different shapes of CDS curves with chosen parameters. He does not use actual data to test the performance of the model.

We follow the same approach and take the equity process as a primitive state variable. The stochastic process describing the stock price is given in expression (5). The stopping time when the equity value crosses the barrier with no jumps is defined by

$$\tau_{NJ} = \inf\{t; S(t) \le B_t \text{ and } N_t = 0 \mid S(0) > B_0\}$$

In this case, the recovery rate is denoted by R_{NJ}. In the second case, the stock is above the barrier and a jump occurs. The stopping time is defined by

$$\tau_{J} = \inf\{t; N_t = 1 \text{ and } S(u) > B_u \text{ for all } u < t \mid S(0) > B_0\}$$

In this case, the recovery rate is denoted by R_J. The time to default is defined as the minimum of the stopping times

$$\tau = \min(\tau_{NJ}, \tau_{J})$$

We consider three cases: (a) the barrier is constant; (b) the barrier is described by the stochastic process as in Trinh (2004); and (c) the barrier is described by a random variable, as in CreditGrades (2002).

3.1 Constant Barrier

In this model, the barrier is assumed to be a constant. The firm surviving until time t depends on (a) the barrier not being crossed and (b) no jump. The probability of surviving until time T is given by

$$P(\tau > t) = \exp(-\lambda t)[N(w_1) - (B/S)^{2\nu} N(-w_2)] \tag{7}$$

where[3]

$$
\begin{aligned}
w_1(t) &= \{\ln(S/B) + \mu t\}/\sigma_S\sqrt{t}, \\
w_2(t) &= \{\ln(S/B) - \mu t\}/\sigma_S\sqrt{t}, \\
\mu &= r - \delta + \lambda - \sigma_S^2/2, \\
\upsilon &= \mu/\sigma_S^2,
\end{aligned}
$$

and $N(\cdot)$ is the cumulative normal distribution function.

For a CDS with payment dates $T_j, j = 1, ..., n$, the value of the CDS premium leg is given by

$$PV_B = S_{CDS} \sum_{j=1}^{n} Z(0, T_j)\ \Delta_j\ P(\tau > T_j)$$

where S_{CDS} is the swap premium, $Z(0, T_j)$ is the price of a risk-free zero-coupon bond with maturity[4] T_j, and $\Delta_j \equiv T_j - T_{j-1}$.

To determine the present value of the protection leg, we will need to evaluate an expression of the form

$$G(T) = \int_{s=0}^{T} e^{-(r+\lambda)s} f(s) ds$$

where $f(s)$, the density function of default occurring between $(s, s + ds)$ is given by

$$f(t) = \frac{b}{\sigma_s t^{3/2}} \phi(w_1)$$

where $\phi(\cdot)$ is the normal density function; and $b \equiv \log(S/B) > 0$.

One can derive

$$G(T) = (B/S)^{\nu - \beta_1} N(-a_1) + (B/S)^{\nu + \beta_1} N(-a_2) \tag{8}$$

[3] The results in this section are all well known - see Bielecki and Rutkowski (2002), chapter 3.

[4] Note that there is a slight inconsistency here. In deriving the survival probabilities we take the term structure as flat. However, for pricing we use the current term structure of risk-free rates. To calculate the probability of survival over T periods, we use the T period rate of interest.

where

$$
\begin{aligned}
a_1 &\equiv \{\ln(S/B) + \beta T\}/\sigma_S\sqrt{T}, \\
a_2 &\equiv \{\ln(S/B) - \beta T\}/\sigma_S\sqrt{T}, \\
\beta &\equiv [\mu^2 + 2(r+\lambda)\sigma_S^2]^{1/2}, \\
\beta_1 &\equiv \beta/\sigma_S^2.
\end{aligned}
$$

Default over the interval $(0, T]$ will depend on either (a) a jump occuring when the barrier has not yet been crossed or (b) no jump but the barrier is crossed. By assumption we rule out the event of a jump occurring at the moment when the barrier is crossed. These events are mutually exclusive. The present value of event (a) is given by

$$L_a = \frac{\lambda}{r+\lambda}[1 - e^{-rT}P(\tau > T)] - \frac{\lambda}{r+\lambda}G(T),$$

and the present value of event (b) is given by

$$L_b = \int_0^T e^{-(r+\lambda)s} f(s)ds = G(T).$$

The value of the protection leg is given by

$$PV_P = (1 - R_J)L_a + (1 - R_{NJ})L_b. \tag{9}$$

The value of a credit default swap is

$$V(t) = PV_P(t) - PV_B(t).$$

The premium S_{CDS} is set such that the initial value of the swap is zero: $V(0) = 0$.This general expression for the value of a credit default swap is also applicable to the next two models. The value of the CDS premium leg, $PV_B(t)$,is also the same for all three models.

3.2 Stochastic Barrier

In this model, the barrier is described by a lognormal stochastic process given by expression (6). The presence of a stochastic barrier involves only a minor extension of the results given in the last section. The case of a constant barrier is nested within this model. The probability of surviving until time T is now given by

$$P(\tau > t) = \exp(-\lambda t)[N(w_1) - (B/S)^{2\nu} N(-w_2)] \tag{10}$$

where[5]

$$\begin{aligned} w_1(t) &= \{\ln(S/B) + \mu t\}/\sigma\sqrt{t}, \\ w_2(t) &= \{\ln(S/B) - \mu t\}/\sigma\sqrt{t}, \\ \mu &= r - \delta + \lambda - \mu_B - \sigma_S^2/2 + \sigma_B^2/2, \\ \upsilon &= \mu/\sigma^2, \sigma^2 = \sigma_S^2 + \sigma_B^2. \end{aligned}$$

We now calculate the present value of receiving one dollar if default occurs over the interval $(0, T]$. Let

$$G(T) = \int_{s=0}^{T} e^{-(r+\lambda)s} f(s) ds$$

Hence

$$G(T) = (B/S)^{\gamma - \beta_1} N(-a_1) + (B/S)^{\gamma + \beta_1} N(-a_2), \tag{11}$$

where

$$\begin{aligned} a_1 &= \{\ln(S/B) + \beta T\}/\sigma\sqrt{T}, \\ a_2 &= \{\ln(S/B) - \beta T\}/\sigma\sqrt{T}, \\ \beta &= [\mu^2 + 2(r + \lambda)\sigma^2]^{1/2}, \\ \beta_1 &= \beta/\sigma^2. \end{aligned}$$

The value of the protection leg is given by

$$PV_P = (1 - R_J)\{\frac{\lambda}{r + \lambda}[1 - e^{-rT} P(\tau > T)] - \frac{\lambda}{r + \lambda} G(T)\} + (1 - R_{NJ}) G(T) \tag{12}$$

Note that if the two recovery rates are equal, this expression is equivalent to the expression given in Trinh (2004).

[5] If we allowed the Brownian motions to be correlated, there would be a correlation term in the drift μ and the volatility σ.

3.3 Uncertain Barrier

Now let the barrier B be described by a log normally distributed random variable[6]

$$\tilde{B} = B \exp(\tilde{u}\sigma_u - \sigma_u^2/2), \tag{13}$$

where $\tilde{u}$ is a zero mean, unit variance normally distributed random variable. The mean of $\tilde{B}$ is B and the standard deviation is $B[\exp(\sigma_u^2) - 1]^{1/2}$. The probability of no default over the time T, using expression (7), is given by

$$P(\tau > T) = \exp(-\lambda T) E[N(w_1) - (\tilde{B}/S)^{2\nu} N(-w_2)],$$

where the expectation is taken over the barrier distribution. Therefore

$$P(\tau > T) = \exp(-\lambda T)[N_2(b, b_1, \rho) - (B/S)^{2\nu} \exp(-v\sigma_u^2 + 2v^2\sigma_u^2)\ N_2(b^*, b_2, -\rho)], \tag{14}$$

where

$$\begin{aligned} b &= [\ln(S/B) + \sigma_u^2/2]/\sigma_u, \\ b^* &= [\ln(S/B) + \sigma_u^2/2 - 2v\sigma_u^2]/\sigma_u, \\ b_1 &= [(\ln(S/B) + \mu T) + \sigma_u^2/2]/(\sigma_S^2 T + \sigma_u^2)^{1/2}, \\ b_2 &= [(-\ln(S/B) + \mu T) + \sigma_u^2/2]/(\sigma_S^2 T + \sigma_u^2)^{1/2}, \\ \rho &= \sigma_u/(\sigma_S^2 T + \sigma_u^2)^{1/2}, \end{aligned}$$

and $N_2(\cdot,\cdot,\cdot)$ is the bivariate cumulative normal distribution function[7].

To compute the protection leg, we must evaluate a term of the form

$$G(T) = E[(B/S)^{v-\beta_1} N(-a_1) + (B/S)^{v+\beta_1} N(-a_2)]$$

Hence

$$\begin{aligned} G(T) &= (B/S)^{c_1} \exp(-c_1\sigma_u^2 + 2c_1^2\sigma_u^2) N_2(b_1^*, b_3, -\rho) \\ &\quad + (B/S)^{c_2} \exp(-c_2\sigma_u^2 + 2c_2^2\sigma_u^2) N_2(b_2^*, b_4, -\rho) \end{aligned}$$

[6] This assumption is made in CreditGrades (2002).

[7] A numerical Matlab code written by Professor Alan Genz of Washington State University is used to evaluate this function.

where

$$
\begin{aligned}
c_1 &= \upsilon - \beta_1, \\
c_2 &= \upsilon + \beta_1, \\
b_1^* &= [\ln(S/B) + \sigma_u^2/2 - 2c_1\sigma_u^2]/\sigma_u, \\
b_2^* &= [\ln(S/B) + \sigma_u^2/2 - 2c_2\sigma_u^2]/\sigma_u, \\
b_3 &= [(-\ln(S/B) - \beta T) - \sigma_u^2/2 + 2c_1\sigma_u^2]/(\sigma_S^2 T + \sigma_u^2)^{1/2}, \\
b_4 &= [(-\ln(S/B) + \beta T) - \sigma_u^2/2 + 2c_2\sigma_u^2]/(\sigma_S^2 T + \sigma_u^2)^{1/2}.
\end{aligned}
$$

The value of the protection leg is given by

$$PV_P = (1 - R_J)\{\frac{\lambda}{r+\lambda}[1 - e^{-rT}P(\tau > T)] - \frac{\lambda}{r+\lambda}G(T)\} + (1 - R_{NJ})G(T)$$

4 Data and Empirical Methodology

4.1 Data

To empirically evaluate our models, we require firm-level data on credit default swaps, equity, and the term structure of risk-free interest rates. In addition, we want to relate estimated jump intensities, default barriers and barrier volatilities to firm-specific variables related to default risk, such as credit ratings, equity volatility, and balance sheet information. We obtain these variables from several major data sources, which are explained below.

We obtain default swap premia from ValuSpread Credit provided by Lombard Risk Systems, which assembles information on credit derivatives from selected leading credit derivatives market-makers. Based on collected quotes, Lombard Risk Systems provides the daily average quotes for thousands of reference entities. In this paper, we include CDS quotes on non-Sovereign U.S. bond issuers denominated in U.S. dollars with reference issues ranked senior. In addition, we focus on 3-year and 5-year CDS data with modified restructuring clauses because they are the most liquid CDS contracts traded in the credit derivatives market. The sample period is January 2003 to May 2005.

Although Lombard Risk Systems has applied a statistical procedure to filter out outliers and stale quotes, we still find a significant number of abnormal quotes in the data. We apply several filters to further clean up the data. First, we eliminate stale quotes by keeping only the first observation of a sequence of the same quotes. Second, we apply an exponentially weighted 5-day moving average to fit the time series of daily quotes for each reference entity. A quote is deemed abnormal and eliminated if the fitting error for that quote lies beyond two standard deviations of fitting errors. Finally, we manually check the data on firms with abnormal quotes to make sure that we do not eliminate those quotes because of abnormal observations on the first five days.

After cleaning up the data, we restrict our data set by eliminating firms with CDS quotes for less than one year. In addition, we exclude all firms in financial and utility industries according to the North American Industry Classification System (NAICS) codes. Firms in the financial industry are excluded because their leverage ratios (defined below) are not comparable to those of firms in other industries, and because we want to relate our estimated default measures to leverage ratios. Firms in the utility industry are excluded because they are highly regulated and their default features are different from firms in other industries.

We use the CRSP daily stock file for equity data and the COMPUSTAT industrial quarterly for balance sheet information. The variables used in our default models are constructed as follows:

Equity price: A time series of equity prices is constructed for each company by multiplying the daily closing equity price with the accumulative price adjustment factor from CRSP.

Equity volatility: A time series of equity volatility is computed for each company using the standard deviation of daily returns obtained from CRSP for the 180 days prior to (but not including) a CDS quote.

Dividend yield: Quarterly dividend yields for each company are obtained from COMPUSTAT. To avoid a forward-looking bias, we use the dividend yield of the quarter prior to a CDS quote.

Risk-free bond yields: The interest rate swap curve is an obvious choice to proxy the risk-free rates due to industry practice. However, interest rate swaps contain credit premia because the floating leg is indexed to LIBOR, which is a default-risky interest rate (Sundaresan (1991) and Collin-Dufresne and Solnik (2001)). The swap curve might over-estimate the risk-free yield curve. The treasury yield curve would be an alternative choice. However, because of repo specials associated with "on-the-run" and "just-off-the-run" treasuries, the treasury yield curve might under-estimate the risk-free yield curve. In this study, we use daily yield curves of zero-coupon bonds constructed by Gurkaynak, Sack, and Wright (2006) at the Federal Reserve Board to proxy the risk-free yield curve. They construct daily yield curves from treasury data excluding the "on-the-run" and "just-off-the-run" treasuries. The estimated yield curves are less susceptible to repo specials.

In addition to variables used in the default models, we follow empirical studies on default risk (Campbell and Taksler (2003) , and Bakshi, Madan, and Zhang (2004), etc.) and construct firm-specific variables for each company and relate them to our estimated jump intensities, default barriers, and barrier volatilities. Since parameters in our models are assumed to be constant, the averages of the firm-specific variables during the sample period are constructed as follows:

Credit rating: Quarterly credit ratings for each company are obtained from COMPUSTAT based on the Standard and Poor's long-term domestic issuer credit ratings. The simple average of the credit rating for each firm during the sample period is calculated.

Volatility: Equity volatilities are computed for each firm using the standard deviation of daily equity returns during the sample period.

Leverage ratio: The leverage ratio is defined as the book value of long-term debt (COMPUSTAT quarterly item 51) divided by firm value. The firm value is the sum of the book value of long-term debt and the market value of equity, which is computed from CRSP as the average daily market values of equity in a quarter. A simple average of quarterly leverage ratios for each company is calculated.

Book-to-market ratio: The book to market ratio is defined as the book value of equity (COMPUSTAT quarterly item 59) divided by the market value of equity. A simple average of quarterly book-to-market ratios for each company is calculated.

Profitability: Profitability is defined as one minus operating income before depreciation (COMPUSTAT quarterly item 21) divided by the net sales (COMPUSTAT quarterly item 2). A simple average of profitability measures for each company is calculated.

These variables have been used in the credit risk literature to explain cross-firm default measures. Credit ratings are used to assess the credit quality of firms. Campbell and Taksler (2003) demonstrates that equity volatility helps to determine corporate bond spreads in the cross section. Leverage is a key ingredient in the structural models (Merton (1974), Longstaff and Schwartz (1995), and Collin-Dufrene and Goldstein (2001)) to capture firm-level stress. Fama and French (1992) shows that firms with high book to market ratios are relatively more distressed with poor cash flow prospects. Titman and Wessels (1988) shows that profitability reflects a firm's ability to honor debt obligations out of its operating income. Therefore, high levels of leverage and book-to-market ratios indicate distressed firms, and high levels of profitability indicate healthy firms.

After matching CDS data with equity and balance sheet data, we have 240 companies left in our study. The Appendix lists all the companies and their corresponding average credit ratings from Standard & Poor's during the sample period. The industrial and credit rating distributions of the 240 companies are presented in Table 1. The sample firms in our study represent a large number of industrial sectors with more than 50% of the firms in the manufacturing industry. The credit ratings of 88% of the firms lies between A and BB. It is consistent with alternative data sources used in other empirical studies (Ericsson, Jacobs, and Oviedo (2005), and Zhang, Zhou, and Zhu (2005)).

Because there are relatively few firms with credit ratings above AA and below BB, we group all firms into three credit rating categories: AAA to A, BBB, and BB and below. For notional convenience, they are denoted by A, BBB, and BB respectively. The daily average 3-year and 5-year CDS premia for the three credit categories are plotted in Figure 1. It shows that the CDS premia were declining during the sample period.

Table 2 summarizes the means and standard deviations of 3-year and 5-year CDS premia for the three credit categories. Average 5-year CDS premia are higher than average 3-year CDS premia across credit categories. Across maturities, the average CDS premia for BBB-rated firms are two times higher than those for A-rated firms, and the average CDS premia for BB-rated firms are ten times higher than those for A-rated firms. CDS premia also exhibit larger variations for low credit categories than those for high credit categories. Table 2 also summarizes the means and standard deviations for equity volatilities and balance sheet variables. Cross-firm average leverage ratios, average book-to-market ratios, and average equity volatilities in low credit categories are higher than those in high credit categories. However, cross-firm average profitability does not exhibit the same pattern.

4.2 Empirical Methodology

We implement nonlinear least square regressions to estimate parameters in the equity-based default models. However, we cannot empirically identify either the jump recovery rate, R_J, or the diffusion recovery rate, R_{NJ}. They are both fixed at 44%, the historical average recovery rate reported by Standard & Poor's. In addition, the drift parameter, μ_B, and the jump intensity parameter, λ, in the stochastic barrier model, cannot be separately identified. We fix μ_B at zero. Therefore, the parameters to be estimated are as follows: the jump intensity λ, and the default barrier B in the constant barrier model; the jump intensity λ, the default barrier B, and the barrier volatility σ_B in the stochastic barrier model; the jump intensity λ, the default barrier B, and the barrier volatility σ_u in the uncertain barrier model. Given the setup, the constant barrier model is embedded in both the stochastic barrier and uncertain barrier models.

We estimate the parameters for each firm by minimizing the sum of squared pricing errors for the entire sample. Specifically, let $CDS_{i,t}$ and $\widehat{CDS_{i,t}}$ $(i = 1, 2)$ denote the observed and model-implied 3-year $(i = 1)$ and 5-year $(i = 2)$ CDS premia for date t for a given firm. We minimize the sum of squared pricing errors by

$$SSE = \min_{\theta} \sum_{t=1}^{T} \sum_{i=1}^{2} \left(CDS_{i,t} - \widehat{CDS_{i,t}} \right)^2$$

After obtaining the estimates for jump intensities, default barriers and barrier volatilities, we conduct cross-firm regression analysis to study the relationship between the estimated parameters and firm-specific variables related to default risk, such as credit ratings, equity volatilities, and accounting variables.

5 Estimation Results

5.1 Parameter Estimates and Model Comparison

Because of the large number of firms included in our study, we summarize the results by reporting the cross-firm average of parameter estimates for each credit category. A Newey-West (1987) consistent variance covariance estimator with five lags is used to calculate the test statistics for parameter estimates. Table 3 reports the parameter estimates. Since stocks are traded at different price levels for different firms, we cannot directly compare estimated default barriers for different firms. Therefore, we normalize the estimated default barrier for each firm by dividing it by the average stock price during the sample period. The cross-firm average of estimated B/S ratios for each credit category are also reported in Table 3.

For the constant barrier model, the average estimated B/S ratio is 0.051, 0.063, and 0.080 for credit categories A, BBB, and BB respectively. The cross-firm average jump intensity estimate is 0.4%, 1.0%, and 3.7% for credit categories A, BBB, and

BB respectively. Both the estimated B/S ratio and jump intensity increases as the credit quality of firms declines. In addition, the default barrier estimates are statistically significant at the 1% level for 97.4% of firms in credit category A, 98.1% of firms in credit category BBB, and 92.9% of firms in credit category BB respectively. The jump intensity estimates are statistically significant at the 1% level for 98.7% of firms in credit category A, 99.1% of firms in credit category BBB, and 100% of firms in credit category BB respectively.

The estimated B/S ratio and jump intensity exhibit a similar cross-credit category pattern in the stochastic barrier and uncertain barrier models. Barrier uncertainty increases default risk given other factors unchanged. It is no surprise that when the barrier uncertainty is introduced in the stochastic barrier and uncertain barrier models, the estimated B/S ratio for each credit category is in general smaller than that estimated from the constant barrier model. Specifically, the average estimated B/S ratio for credit category A declines from 0.051 in the constant barrier model to 0.022 in the stochastic barrier model and 0.033 in the uncertain barrier model. In addition, the estimated jump intensity from the stochastic barrier model for different credit categories is almost one half the magnitude as it is for the constant barrier model. But the average jump intensity estimate for each credit category for the uncertain barrier model is almost the same as that estimated for the constant barrier model.

The average barrier volatility estimates in the stochastic barrier model do not exhibit clear cross-credit category patterns. They are statistically significant at the 1% level for more than 94% of firms in each credit category. The average barrier volatility estimates in the uncertain barrier model in general decline in tandem with the credit quality of firms. They are statistically significant at the 1% level for more than 87% of firms in credit category A, 81% of firms in credit category BBB, and 53% of firms in credit category BB.

To assess the in-sample fit of the models, we compute pricing errors of 3-year and 5-year CDS premia as differences between observed CDS premia and model-implied CDS premia. The cross-firm average of the mean absolute deviation (MAD) and the root mean squared error (RMSE) of pricing errors of 3-year and 5-year CDS premia for each credit category are reported in panel A of Table 4. In addition, we regress observed CDS premia on model-implied CDS premia for each firm, and report the cross-firm average of R^2s for each credit category. According to the MAD and RMSE criteria, all three models fit CDS premia better for firms in high credit classes than those in low credit classes. In addition, when barrier uncertainty is introduced in the stochastic barrier and uncertain barrier models, the average pricing errors for 3-year and 5-year CDS premia are smaller for each credit class. Furthermore, the decline in pricing errors is larger in the stochastic barrier model than that in the uncertain barrier model. The results show that the stochastic barrier model performs the best among the three models in terms of in-sample fitting.

The reported R^2s from the regressions of observed CDS premia on model-implied CDS premia show that the stochastic barrier model performs the best with average R^2s of 56%, 56%,and 64% for 5-year CDS premia in credit category A, BBB, and BB respectively. The average R^2s calculated from the stochastic barrier models are 16% to 26% higher than those calculated form the constant barrier models, and 8% to 20% higher than those calculated from the uncertain barrier model.

To formally test the models, we implement the standard likelihood ratio test for the constant barrier model against the stochastic and uncertain barrier models since the first model is embedded in the latter two models. To test the stochastic barrier model against the uncertain barrier model, we implement a likelihood ratio based Vuong (1989) test for non-nested models. The test results are reported in panel B of Table 4. At the 1% significance level, the stochastic barrier model is significantly better than the constant barrier model for 94.9% of firms in credit category A, 92.5% of firms in credit category BBB, and 98.2% of firms in credit category BB. The uncertain barrier model is also significantly better than the constant barrier model for 91.0% of firms in credit category A, 87.7% of firms in credit category BBB, and 71.4% of firms in credit category BB. The Vuong test shows that the stochastic barrier model is significantly better than the uncertain barrier model for 84.6% of firms in credit category A, 83.0% of firms in credit category BBB, and 91.1% of firms in credit category BB. Therefore, the stochastic barrier model performs the best among the three models we have estimated.

We also compare the out-of-sample forecasting performance of the three models. The procedure of out-of-sample forecasts is as follows. At each time t, we estimate parameters in the three models with data up to and including date t, and use the estimated parameters at time t with the equity price, equity volatility, dividend yield, and interest rates at time $t+1$ to compute the predicted CDS premia at time $t+1$. Therefore, only the estimated parameters are used "out-of-sample", while other inputs to the models are kept up to date. The average of the MAD and RMSE of the forecasting errors for each credit category are reported in Table 5. According to the MAD and RMSE criteria, the stochastic barrier model performs marginally better than the constant barrier model across credit categories, and both constant barrier and stochastic barrier models out-perform the uncertain barrier model.

We have demonstrated the in-sample and out-of-sample performance of the three models. There remains the question of how the estimated default barrier, jump intensity, and barrier volatility are related to firm-specific variables which can explain cross-firm default risk in the literature. We consider three sets of variables: credit ratings, equity volatility, and accounting variables including the leverage ratio, the book-to-market ratio, and the profitability. Next we investigate the relationship between default-related parameter estimates from the models and the three sets of variables.

5.2 Default Barrier, Jump Intensity and Barrier Volatility

5.2.1 Pooled Regressions

Since we cannot directly compare the estimated default barrier across firms, we use estimated default barrier and average equity price during the sample period to calculate the B/S ratio for each firm. In addition, we calculate the average credit rating and accounting variables for each firm using quarterly observations during the sample period. We also calculate the equity volatility for each firm as the standard deviation of equity returns during the sample period. Then we run ordinary least square (OLS) regressions with the cross-firm data to study how the estimated B/S ratio, jump intensity, and barrier volatilities are related to credit ratings, equity volatility, and accounting variables. The regression results are reported in Table 6. Coefficients are reported with t-statistics below them in parentheses, and bold face is used to indicate coefficients that are significant at the 1% level or better. The t-statistics are calculated based on White (1980) heteroscedasticity-consistant covariance estimators.

In regressions of the B/S ratios estimated from the three models, several observations are notable. First, the dummy variable for credit category BB is positive and statistically significant across models, indicating that the B/S ratio is higher for a firm with credit rating BB than that for a firm with credit rating A. Second, equity volatility is statistically significant across models, and it is negatively related to the B/S ratio. After we control for credit ratings and accounting variables, firms may have the same default risk. Therefore, the negative relationship between the B/S ratio and equity volatility might be due to the simple fact that increasing the B/S ratio and decreasing equity volatility at the same time could lead to the same default risk. Third, accounting variables in most cases have correct signs, and only the leverage ratio is positive and statistically significant across models. It indicates that the leverage ratio captures some information that is not contained in the credit ratings and equity volatility. Fourth, credit ratings, equity volatility, and accounting variables have combined adjusted R^2s of 29.2%, 43.8%, and 25.4% in the constant barrier, stochastic barrier, and uncertain barrier models respectively. The regression results show that our estimated B/S ratios capture cross-firm distress.

In regressions of the jump intensity estimated from the three models, the dummy variable for credit category BB is positive and statistically significant. The results show that a firm with credit rating BB has a higher jump risk than a firm with credit rating A. In addition, the jump intensity is positively related to equity volatility, indicating that a firm with high equity volatility has a higher probability of jump risk. Furthermore, even after controlling for credit ratings and equity volatility, the jump intensity is positively related to the leverage ratio. The combined explanatory power of credit ratings, equity volatility, and accounting variables on the jump intensity is 75.7%, 54.2%, and 73.8% for the constant barrier, stochastic barrier, and uncertain barrier model, respectively. The estimated jump intensity is also related to cross-firm distress.

In regressions of the barrier volatility estimated from the stochastic barrier model, dummy variables for credit rating BBB and BB are negative and the dummy variable for credit rating BB is statistically significant. The results suggest that the estimated barrier volatility is lower for low quality firms. A positive and statistically significant coefficient of equity volatility indicates that barrier volatility is positively related to equity volatility. In regressions of the barrier volatility estimated from the uncertain barrier model, only the coefficient of the leverage ratio is statistically significant. The explanatory power is 10.9% and 6.9% for the barrier volatility estimated from the stochastic barrier and uncertain barrier model, respectively.

5.2.2 Regressions within Credit Category

Thus far we have investigated the relationship between the parameter estimates from the models and variables related to cross-firm default risk from pooled regressions with a fixed effect for each credit category. An important question is whether the relationship we find in the previous section just reflects cross-credit category variation. Next we run regressions within each credit category to study whether the estimated parameters also capture cross-firm variation of default risk within a credit category. The regression results are presented in Table 7.

In regressions of the estimated B/S ratios from the three models, the coefficient of equity volatility is statistically significant. The negative sign might reflect the negative relationship between the default barrier and equity volatility for any given default risk. The accounting variables have expected signs in most regressions. But they are not significant except in the case of the regression of the B/S ratio estimated from the stochastic barrier model within the credit category BB. The leverage ratio is positive and statistically significant.

In regressions of the estimated jump intensity, the coefficient of equity volatility is positive and statistically significant. It indicates that, within each credit category, a firm with high equity volatility is usually associated with a higher jump intensity. For a few cases in credit category A and BB, the estimated jump intensity is positively related to the leverage ratio.

In regressions of the estimated barrier volatility from the stochastic barrier and uncertain models, only the coefficient of equity volatility is statistically significant for all credit categories. The coefficients are mostly positive except in the case of the uncertain barrier model within credit category BB.

In summary, the estimated B/S ratio, jump intensity, and barrier volatility from the three models are related to firm-specific variables that capture cross-firm default variation. Specifically, they are related to equity volatility and leverage ratios across credit ratings and within each credit category.

5.3 Robustness

We now address the robustness of our parameter estimates. We consider changes in the number of days used to compute equity volatility. At each day, we compute the equity volatility of a firm using the standard deviation of daily equity returns for the 90 and 270 days prior to (not including) that day. We then re-run the NLS regressions with the two different volatility estimates. The parameter estimates are presented in Table 8. The results show that the estimates of the jump intensity and barrier volatility in the three models are robust to the changes. However, the estimate of the default barrier is lower when we use a longer time window of equity data to compute the equity volatility for each firm. This pattern is consistent across models and credit categories. In addition, we report the in-sample pricing errors of the models in Table 9. The results show that the stochastic barrier model still performs the best among the three models with the smallest average pricing errors across credit categories. Another notable result is that the pricing error is smaller when we use a longer time window to compute the equity volatility for each firm. The results are consistent across models and credit categories. It suggests that a fairly long time window is needed to properly measure the equity volatility that is related to pricing CDS premia.

6 Conclusion

In this paper, we examine three equity-based default models with three different specifications of default barrier to study the nonlinear relationship between equity and CDS prices. With cross-firm CDS premia and equity information, we are able to estimate and compare the three models. We find that the stochastic barrier model performs the best in terms of both in-sample fit and out-of-sample forecasting ability for CDS premia. In addition, the estimated default barrier, jump intensity and barrier volatility are related to firm-specific variables, such as credit ratings, equity volatility, and leverage ratios, that are used to explain cross-firm default variations. Our results are robust to the length of time window we use to compute the equity volatility of a firm. This paper shows that equity information helps price CDS premia.

A Appendix: List of companies used in the study

Company Name	CR	Company Name	CR
Agilent Technologies Inc	BB	Beazer Homes Usa Inc	BB
Alcoa Inc	A	Ca Inc	BBB
Amerisourcebergen Corp	BB	Conagra Foods Inc	BBB
Albertson's Inc	BBB	Cardinal Health Inc	A
Abbott Laboratories	AA	Cameron International Corp	BBB
Archer-Daniels-Midland Co	A	Caterpillar Inc	A
American Financial Group Inc	BBB	Clear Channel Communications	BBB
Hess Corp	BBB	Cendant Corp	BBB
Applied Materials Inc	A	Chiron Corp	BBB
Amgen Inc	A	Chemtura Corporation	BB
Amkor Technology Inc	B	Colgate-Palmolive Co	AA
Apache Corp	A	Commercial Metals	BBB
Anadarko Petroleum Corp	BBB	Comcast Corp	BBB
Air Products Chemicals Inc	A	Cummins Inc	BB
Arvinmeritor Inc	BB	Conocophillips	A
Arrow Electronics Inc	BBB	Costco Wholesale Corp	A
American Standard Cos Inc	BBB	Campbell Soup Co	A
Ashland Inc	BBB	Computer Sciences Corp	A
Alltel Corp	A	Csx Corp	BBB
Avon Products	A	Cooper Tire Rubber Co	BBB
Avnet Inc	BBB	Centurytel Inc	BBB
At T Wireless Services Inc	BBB	Centex Corp	BBB
Autozone Inc	BBB	Cvs Corp	A
Boeing Co	A	Cytec Industries Inc	BBB
Baxter International Inc	A	Citizens Communications Co	BBB
Best Buy Co Inc	BBB	Dana Corp	BB
Brunswick Corp	BBB	Dillards Inc -Cl A	BB
Black Decker Corp	BBB	Deere Co	A
Baker Hughes Inc	A	Dell Inc	A
Bj Services Co	BBB	D R Horton Inc	BB
Bellsouth Corp	A	Danaher Corp	A
Bristol-Myers Squibb Co	A	Disney (Walt) Co	BBB
Burlington Northern Santa Fe	BBB	Diamond Offshre Drilling Inc	A
Bowater Inc	BB	Dover Corp	A
Burlington Resources Inc	BBB	Dow Chemical	A
Boston Scientific Corp	BBB	Delphi Corp	BB
Anheuser-Busch Cos Inc	A	Darden Restaurants Inc	BBB
Borgwarner Inc	BBB	Devon Energy Corp	BBB

Company Name	CR	Company Name	CR
Dynegy Inc	B	Intl Paper Co	BBB
Electronic Data Systems Corp	BBB	Interpublic Group Of Cos	BB
Equifax Inc	A	Juniper Networks Inc	B
Eastman Kodak Co	BBB	Jones Apparel Group Inc	BBB
Eastman Chemical Co	BBB	Nordstrom Inc	A
Emerson Electric Co	A	Kellogg Co	BBB
El Paso Corp	B	Kb Home	BB
Eaton Corp	A	Kraft Foods Inc	A
Ford Motor Co	BBB	Kerr-Mcgee Corp	BBB
Freeport-Mcmoran Cop Gold	B	Kinder Morgan Energy -Lp	BBB
Federated Dept Stores	BBB	Coca-Cola Co	A
Fedex Corp	BBB	Kroger Co	BBB
Fmc Corp	BBB	Knight-Ridder Inc	A
Fortune Brands Inc	A	Kohl's Corp	A
Sprint Nextel Corp	BBB	Liberty Capital	BB
Forest Oil Corp	BB	Lear Corp	BB
Gillette Co	AA	Liz Claiborne Inc	BBB
Gannett Co	A	Lilly (Eli) Co	AA
General Dynamics Corp	A	Lockheed Martin Corp	BBB
General Mills Inc	BBB	Lowe's Companies Inc	A
Great Lakes Chemical Corp	BBB	Louisiana-Pacific Corp	BB
Corning Inc	BB	Limited Brands Inc	BBB
Georgia-Pacific Corp	BB	Lucent Technologies Inc	B
Gap Inc	BB	Southwest Airlines	A
Goodrich Corp	BBB	Lyondell Chemical Co	B
Goodyear Tire Rubber Co	B	Manpower Inc/Wi	BBB
Halliburton Co	BBB	Marriott Intl Inc	BBB
Hasbro Inc	BB	Masco Corp	BBB
Hca Inc	BB	Mattel Inc	BBB
Home Depot Inc	AA	May Department Stores Co	BBB
Harrahs Entertainment Inc	BBB	Mandalay Resort Group	BB
Hilton Hotels Corp	BBB	Mcdonald's Corp	A
Honeywell International Inc	A	Mckesson Corp	BBB
Starwood Hotels Resorts Wrld	BB	Medtronic Inc	AA
Hewlett-Packard Co	A	Mgm Mirage	BB
Humana Inc	BBB	3m Co	AA
Intl Business Machines Corp	A	Motorola Inc	BBB
Imc Global Inc	B	Merck Co	AA
Intl Game Technology	BBB	Marathon Oil Corp	BBB
Ikon Office Solutions	BB	Meadwestvaco Corp	BBB
Intel Corp	A	Maytag Corp	BBB

Company Name	CR	Company Name	CR
Newmont Mining Corp	BBB	Solectron Corp	B
Nike Inc -Cl B	A	Sonoco Products Co	A
Neiman-Marcus Group Inc	BBB	Standard Pacific Cp	BB
Northrop Grumman Corp	BBB	Staples Inc	BBB
Norfolk Southern Corp	BBB	Constellation Brands -Cl A	BB
Newell Rubbermaid Inc	BBB	Sunoco Inc	BBB
Nextel Communications Inc	BB	Sun Microsystems Inc	BBB
Office Depot Inc	BBB	Supervalu Inc	BBB
Owens-Illinois Inc	BB	Safeway Inc	BBB
Olin Corp	BBB	At T Corp	BBB
Omnicom Group	A	Target Corp	A
Occidental Petroleum Corp	BBB	Tenet Healthcare Corp	B
Phelps Dodge Corp	BBB	Tjx Companies Inc	A
Pride International Inc	BB	Toll Brothers Inc	BBB
Pepsico Inc	A	Tribune Co	A
Pfizer Inc	AAA	Sabre Holdings Corp -Cl A	BBB
Procter Gamble Co	AA	Tyson Foods Inc -Cl A	BBB
Parker-Hannifin Corp	A	Tesoro Corp	BB
Pulte Homes Inc	BBB	Time Warner Inc	BBB
Parker Drilling Co	B	Textron Inc	A
Perkinelmer Inc	BB	Unocal Corp	BBB
Caesars Entertainment Inc	BB	Union Pacific Corp	BBB
Ppg Industries Inc	A	Ust Inc	A
Praxair Inc	BBB	United Technologies Corp	A
Qwest Communication Intl Inc	B	Universal Corp/Va	BBB
Ryder System Inc	BBB	Visteon Corp	BB
Reebok International Ltd	BBB	Vf Corp	A
Rohm And Haas Co	BBB	Cbs Corp	BBB
Rockwell Automation	A	Valero Energy Corp	BBB
Rpm International Inc	BBB	Vintage Petroleum Inc	BB
Radioshack Corp	A	Verizon Communications Inc	A
Raytheon Co	BBB	Whirlpool Corp	BBB
Sears Roebuck Co	BBB	Williams Cos Inc	B
At T Inc	A	Waste Management Inc	BBB
Sealed Air Corp	BBB	Wal-Mart Stores	AA
Smithfield Foods Inc	BB	Watson Pharmaceuticals Inc	BBB
Schering-Plough	A	Wyeth	A
Shaw Group Inc	BB	United States Steel Corp	BB
Sherwin-Williams Co	A	Exxon Mobil Corp	AAA
Saks Inc	BB	Xerox Corp	BB
Sara Lee Corp	A	Yum Brands Inc	BB

References

[1] Bakshi, G., D. Madan, and F. Zhang, 2004, "Investigating the Role of Systematic and Firm-Specific Factors in Default Risk: Lessons from Empirically Evaluating Credit Risk Models", Working paper, University of Maryland.

[2] Bank of America (2004), "Guide to Advanced Correlation Products", *Risk*.

[3] Bielecki, T. R. and M. Rutkowski, 2002, *Credit Risk: Modeling, Valuation and Hedging* (Springer, New York).

[4] Blanco, R. S. Brennan and I. Marsh, 2005, "An Empirical Analysis of the Dynamics Relationship Between Investment Grade Bonds and Credit Default Swaps," *Journal of Finance*, 60, 2255-2281.

[5] Cao, Charles, Fan Yu and Zhaodong Zhong, 2007, "The Information Content of Option-Implied Volatility for Credit Default Swap Valuation", Working paper, Penn State University.

[6] Collin-Defresne, P. and B. Solnik, 2001, "On the Term Structure of Default Premia in the Swap and LIBOR Markets", *Journal of Finance*, 56, 1095-1115.

[7] Collin-Defresne, P. and , R. S. Goldstein, 2001, "Do Credit Spreads Reflect Stationary Leverage Ratios", *Journal of Finance*, 56, 1926-1957.

[8] Collin-Defresne, P., R. S. Goldstein and J. S. Martin, 2001, "The Determinants of Credit Spread Changes", *Journal of Finance*, 56, 2177-2207.

[9] CreditGrade (2002), *Technical Document* (RiskMetrics, New York).

[10] CreditMetrics (1997), *Technical Document* (J. P. Morgan, New York).

[11] Campbelle, John Y., and Glen B. Taksler, 2003, "Equity Volatility and Corporate Bond Yields", *Journal of Finance*, 58, 2321-2349.

[12] Elton, Edwin J., Martin J. Gruber, Deepak Agrawal, and Christopher Mann, 2001, "Explaining the Rate Spread on Corporate Bonds", *Journal of Finance*, 56, 247-277.

[13] Eom, Y. H., J. Helwege and J. Huang, 2004, "Structural Models of Corporate Bond Pricing: An Empirical Analysis", *Review of Financial Studies*, 17, 499-544.

[14] Ericsson, J., K. Jacobs and R. Oviedo, 2004, "The Determinants of Credit Default Swap Premiums", Working paper, McGill University.

[15] Fama, E. and K. French, 1992, "The Cross-section of Expected Stock Returns", *Journal of Finance*, 47, 427-465.

[16] Giesecke, K., 2001, "Correlated Defaults with Incomplete Information," Working paper, Humboldt,Universität Berlin,

[17] Gurkaynak, Refet S., Brain P. Sack, and Jonathan H. Wright, 2006, "The U.S. Treasury Yield Curve: 1961 to Present, " Federal Reserve Boards Working paper 2006-28.

[18] Huang, J. and M. Huang, 2003, "How Much of the Corporate Treasury Spread Is Due to Credit Risk?" Working paper, College of Business, Penn State University.

[19] Lehman Brothers, 2003, "Guide to Exotic Credit Derivatives", *Risk*.

[20] Leland, H. E., and K. Toft, 1996,"Optimal Capital Structure, Endogenous Bankruptcy, and the Term structure of Credit Spreads." *Journal of Finance*, 51, pp. 987-1019.

[21] Longstaff, F., S. Mithal and E. Neis, 2005, "The Credit Default Swap Market: Is Credit Protection Priced Correctly?", *Journal of Finance*, 60, 2213-53.

[22] Longstaff, F. A. and E. S. Schwartz, 1995, "A Simple Approach to Valuing Risky and Floating rate Debt", *Journal of Finance*, 50, 789-819.

[23] Mashal, R., M. Naldi, and A. Zeevi, 2003, "Extreme Events and Multi-name Credit Derivatives." *Risk*, pp. 43-54.

[24] Meng, L. and O. Gwilym, 2004, "Credit Default Swaps: theory and Evidence", Working paper, School of Business, University of Wales, Aberystwyth, U. K.

[25] Merton, R. C., 1974, "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates." *Journal of Finance*, 29, pp. 449-470.

[26] Naik, V., M. Trinh, S. Balakrishnan, and S. Sen, 2003, "Hedging Debt with Equity." Lehman Brothers, Quantitative Credit Research.

[27] Newey, W. and K. West, 1987, "A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix", Econometrica, 55, 703-708.

[28] Schonbucher, P. J., 2003, *Credit Derivatives Pricing Models* (John Wiley & Sons, Ltd.London, U.K.).

[29] Sundaresan, Suresh, 1991, "Valuation of swaps", in S. Khoury, ed.: *Recent Developments in International Banking and Finance* (North Holland, Amsterdam).

[30] Titman, S. and R. Wessels, 1998, "The Determinants of Capital Structure Choice", *Journal of Finance*, 43, 1-19.

[31] Trinh, M., 2004, "Orion: A Simple Debt-Equity Model with Unexpected Default." Lehman Brothers, Quantitative Credit Research.

[32] Turnbull, S. M. (2005), "Unresolved Issues in Modeling Credit Risky Assets." *Journal of Fixed Income*, 15, 1, pp 68-87.

[33] Vuong, Quang H., 1989, "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses", *Econometrica*, 57, 307-34.

[34] White, H., 1980, "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity", *Econometrica*, 48, 149-70.

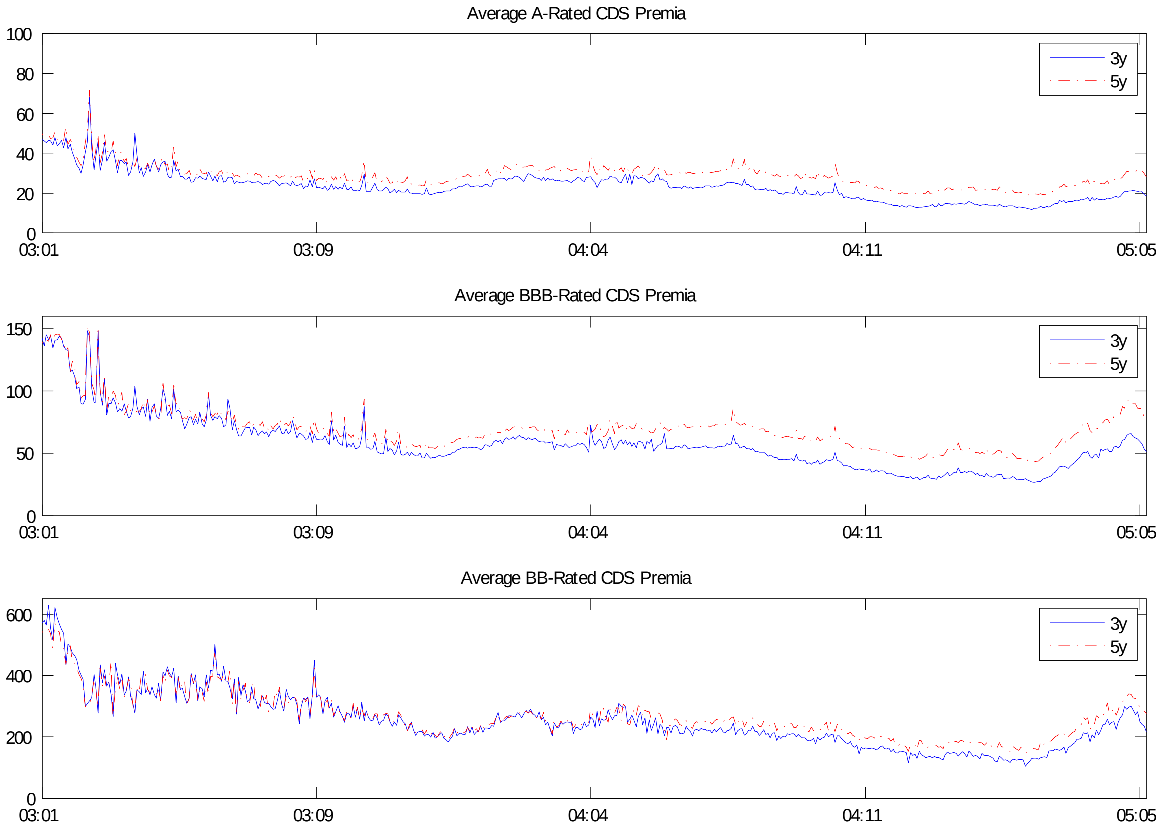
[35] Zhang, B. Y., H. Zhou, and H. Zhu, 2005, "Explaining Credit Default Swap Spreads with Equity Volatility and Jump Risks of Individual Firms." Unpublished paper, Moody's KMV.

[36] Zhou, C., 2001, "The Term Structure of Credit Spreads with Jump Risk", *Journal of Banking and Finance*, 25, 2015-40.

[37] Zhou, C. 2001, "An Analysis of Default Correlations and Multiple Defaults." *Review of Financial Studies*, 14, pp. 555-576.

[38] Zhu, H. (2004), "An Empirical Comparison of Credit Spreads Between the Bond Market and the Credit Default Swap market", Working paper, Bank for International Settlements.

Figure 1: Average 3-year and 5-year CDS Premia for each Credit Class



This graph plots time series of cross-firm averages of 3-year and 5-year CDS premia for credit class A , BBB, and BB. The sample period is January 2003 to May 2005.

Table 1: Industry and Credit Class Distributions

Panel A: Industry Sector

Industry name (NAICS definitions)	number	percentage (%)
Agriculture, Forestry, Fishing and Hunting	16	6.7
Construction	8	3.3
Manufacturing	124	51.7
Wholesale Trade	10	4.2
Retail Trade	26	10.8
Transportation and Warehousing	8	3.3
Information	21	8.8
Professional, Scientific, and Technical Services	8	3.3
Accommodation and Food Services	10	4.2
Others	9	3.8
Total	*240*	*100*

Panel B: Credit Class

Credit rating (Standard & Poor's)	number	percentage (%)
AAA	2	0.8
AA	10	4.2
A	66	27.5
BBB	106	44.2
BB	42	17.5
B	14	5.8
Total	*240*	*100*

Table 2: Summary Statistics

Panel A: CDS Premia

	A	BBB	BB
3-year			
mean (bps)	23.6	58.4	252.4
stdev (bps)	7.6	22.9	92.7
5-year			
mean (bps)	29.2	70.3	268.9
stdev (bps)	6.4	18.8	77.6

Panel B: Equity Volatility

	A	BBB	BB
Volatility			
mean	0.29	0.34	0.47
stdev	0.06	0.07	0.14

Panel C: Accounting Variables

	A	BBB	BB
Leverage			
mean	0.14	0.27	0.43
stdev	0.09	0.14	0.19
Book-to-Market			
mean	0.32	0.54	0.67
stdev	0.22	0.24	0.38
Profitability			
mean	0.79	0.82	0.84
stdev	0.13	0.14	0.12

This table summarizes cross-credit class average and standard deviation of 3-year and 5-year CDS premia (Panel A), equity volatilities (Panel B), and leverage ratios, book-to-market ratios, and profitability (Panel C). The sample period is January 2003 to May 2005.

Table 3: Parameter Estimates

Constant Barrier Model

	A		BBB		BB	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	2.469	97.4%	2.308	98.1%	2.019	92.9%
λ	0.004	98.7%	0.010	99.1%	0.037	100%
$B/\overline{S}$	0.051		0.063		0.080	

Stochastic Barrier Model

	A		BBB		BB	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	1.031	94.7%	1.463	94.6%	2.006	96.2%
σ_B	0.969	96.1%	0.883	94.6%	1.366	94.2%
λ	0.002	94.7%	0.005	75.0%	0.021	76.0%
$B/\overline{S}$	0.022		0.043		0.090	

Uncertain Barrier Model

	A		BBB		BB	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	1.599	73.1%	1.511	68.9%	1.359	48.2%
σ_u	0.707	87.2%	0.672	81.1%	0.515	53.6%
λ	0.004	97.4%	0.009	98.1%	0.035	100%
$B/\overline{S}$	0.033		0.041		0.056	

A non-linear least square regression is applied for each firm. This table reports the cross-firm average of parameter estimates from the constant barrier, stochastic barrier, and uncertain barrier models for each credit rating category. A Newey-West (1987) consistent covariance estimator with five lags is used to compute t-statistics. The percentage of firms with a statistically significant (at 1% level) parameter estimate is also reported for each credit rating category.

Table 4: In-Sample Fit

Panel A: In-Sample Pricing Errors

Constant Barrier Model

	A			BBB			BB		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	5.8	7.5	0.25	18.3	23.9	0.30	66.0	86.1	0.38
CDS_{5y}	5.5	6.8	0.32	17.1	23.3	0.34	57.2	77.5	0.41

Stochastic Barrier Model

	A			BBB			BB		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	4.1	5.2	0.56	13.1	17.3	0.56	45.7	61.3	0.65
CDS_{5y}	4.5	5.7	0.48	14.2	18.9	0.48	44.4	59.2	0.61

Uncertain Barrier Model

	A			BBB			BB		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	4.6	5.8	0.47	15.8	20.5	0.47	62.7	82.3	0.44
CDS_{5y}	4.9	6.2	0.40	16.1	21.7	0.40	56.1	75.9	0.43

Panel B: Statistical Tests

	SB vs. CB sig. (1%)	UB vs. CB sig. (1%)	SB vs. UB sig. (1%)
A	94.9%	91.0%	84.61%
BBB	92.5%	87.7%	83.0%
BB	98.2%	71.4%	91.1%

Panel A reports the cross-firm average of the mean absolute deviation (MAD) and the root mean squared error (RSMSE) of in-sample pricing errors of 3-year and 5-year CDS premia for each credit rating category. The reported numbers are in basis points. The average of R^2s of regressing observed 3-year and 5-year CDS premia on model-implied CDS premia for each credit rating category are also reported in Panel A. The likelihood ratio based test statistics are computed, and the percentage of statistically significant (at 1% level) test statistics for each credit category is reported in Panel B.

Table 5: Out-of-Sample Forecast

Constant Barrier Model

	A		BBB		BB	
	MAD	RMSE	MAD	RMSE	MAD	RMSE
CDS_{3y}	3.8	4.7	10.9	13.5	36.2	47.4
CDS_{5y}	4.9	6.0	12.8	16.0	36.3	47.8

Stochastic Barrier Model

	A		BBB		BB	
	MAD	RMSE	MAD	RMSE	MAD	RMSE
CDS_{3y}	3.5	4.4	10.2	12.6	30.4	40.5
CDS_{5y}	4.6	5.6	11.9	14.9	32.6	42.9

Uncertain Barrier Model

	A		BBB		BB	
	MAD	RMSE	MAD	RMSE	MAD	RMSE
CDS_{3y}	3.8	4.7	32.3	45.0	118.5	132.6
CDS_{5y}	4.8	5.9	34.3	47.6	119.3	133.8

This table reports the cross-firm average of the mean absolute deviation (MAD) and the root mean squared error (RMSE) of out-of-sample forecasting errors of 3-year and 5-year CDS premia for each credit rating category. The reported numbers are in basis points. The procedure of out-of-sample forecasts is as follows: at each time t, we estimate parameters in the three models with data up to and including date t, and forecast the CDS premia at time $t+1$ with estimated parameter at date t and the equity price, equity volatility, dividend yield, and interest rates at date $t+1$.

Table 6: Explaining B/S Ratio, Jump Intensity, and Barrier Volatility

	Constant Barrier		Stochastic Barrier			Uncertain Barrier		
	$\widehat{B}/\overline{S}$	$\widehat{\lambda}$	$\widehat{B}/\overline{S}$	$\widehat{\lambda}$	$\widehat{\sigma}_B$	$\widehat{B}/\overline{S}$	$\widehat{\lambda}$	$\widehat{\sigma}_u$
Credit ratings								
dummy (BBB)	0.012	−0.001	0.012	−0.001	−0.354	0.006	−0.001	0.013
	(1.41)	(−0.51)	(2.20)	(−1.16)	(−2.27)	(0.78)	(−1.14)	(0.27)
dummy (BB)	**0.057**	**0.012**	**0.061**	**0.006**	**−0.359**	**0.041**	**0.011**	−0.091
	(3.95)	(5.66)	(6.14)	(2.79)	(−2.55)	(3.37)	(4.75)	(−1.32)
Equity volatility								
stdev of daily returns	**−0.310**	**0.067**	**−0.092**	**0.041**	**3.382**	**−0.221**	**0.070**	0.081
	(−6.76)	(4.67)	(−3.09)	(5.14)	(3.26)	(−5.43)	(4.78)	(0.34)
Accounting variables								
leverage ratio	**0.067**	**0.036**	**0.068**	**0.020**	0.615	**0.049**	**0.035**	**−0.404**
	(2.58)	(5.59)	(3.71)	(3.65)	(1.93)	(2.37)	(5.27)	(−2.50)
book-to-market ratio	0.032	−0.007	0.021	−0.003	0.061	0.030	−0.007	0.020
	(1.46)	(−1.97)	(1.46)	(−1.13)	(0.15)	(1.58)	(−1.92)	(0.22)
profitability	−0.037	0.001	−0.014	0.000	0.233	−0.038	0.001	0.219
	(−1.34)	(0.36)	(−0.72)	(−0.16)	(0.88)	(−1.72)	(0.36)	(1.96)
Number of obs.	237	237	237	237	237	237	237	237
Adjusted R^2	0.292	0.757	0.438	0.542	0.109	0.254	0.738	0.069
F	17.19	123.28	31.64	47.63	5.81	14.36	112.03	3.93

Using cross-firm data, we regress estimated barrier to price ratios, jump intensities, and barrier volatilities against the variables listed above. A White (1980) heteroscedasticity-consistent covariance estimator is used to compute t-statistics, which appear in parentheses. A bold number indicates that the parameter estimate is statistically significant at the 1% level.

Table 7: Explaining B/S Ratio, Jump Intensity, and Barrier Volatility for Each Credit Class

Panel A: Credit Class A

	Constant Barrier		Stochastic Barrier			Uncertain Barrier		
	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_B$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_u$
Equity volatility								
stdev of daily returns	**−0.429**	**0.014**	**−0.124**	**0.009**	**1.391**	**−0.361**	**0.013**	**2.237**
	(−5.94)	(5.32)	(−2.75)	(4.14)	(2.73)	(−5.74)	(5.46)	(5.46)
Accounting variables								
leverage ratio	0.014	**0.007**	0.000	0.001	0.093	0.000	**0.006**	−0.430
	(0.32)	(3.13)	(−0.01)	(0.88)	(0.35)	(0.01)	(2.97)	(−1.83)
book-to-market ratio	0.090	−0.001	0.067	0.000	−0.098	0.078	−0.001	0.095
	(1.80)	−(1.57)	(2.01)	(−0.29)	−(0.41)	(1.80)	(−1.96)	(0.57)
profitability	−0.047	0.000	−0.030	0.000	0.297	−0.038	0.000	−0.008
	(−1.88)	(0.11)	(−1.36)	(−0.33)	(1.44)	(−1.80)	(0.39)	(−0.04)
Number of obs.	78	78	78	78	78	78	78	78
Adjusted R^2	0.459	0.321	0.328	0.109	0.045	0.470	0.311	0.201

Panel B: Credit Class BBB

	Constant Barrier		Stochastic Barrier			Uncertain Barrier		
	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_B$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_u$
Equity volatility								
stdev of daily returns	**−0.352**	**0.036**	**−0.115**	**0.023**	**0.942**	**−0.266**	**0.036**	**0.722**
	(−5.72)	(5.02)	(−2.50)	(3.71)	(2.93)	(−4.79)	(4.77)	(2.59)
Accounting variables								
leverage ratio	0.052	0.025	**0.060**	0.012	0.212	0.025	0.024	−0.042
	(1.61)	(3.54)	(2.98)	(1.96)	(1.28)	(1.03)	(3.13)	(−0.23)
book-to-market ratio	0.004	−0.002	0.004	−0.001	−0.054	0.004	−0.002	0.039
	(0.19)	(−0.93)	(0.20)	(−0.27)	(−0.38)	(0.20)	(−0.85)	(0.28)
profitability	−0.013	0.003	0.012	−0.001	0.248	−0.025	0.002	0.306
	(−0.58)	(0.92)	(0.76)	(−0.29)	(1.59)	(−1.36)	(0.72)	(2.06)
Number of obs.	105	105	105	105	105	105	105	105
Adjusted R^2	0.267	0.402	0.098	0.159	0.030	0.232	0.379	0.035

Panel C: Credit Class BB

	Constant Barrier		Stochastic Barrier			Uncertain Barrier		
	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_B$	$\widehat{B/S}$	$\widehat{\lambda}$	$\widehat{\sigma}_u$
Equity volatility								
stdev of daily returns	**−0.271**	**0.095**	−0.094	**0.055**	**5.402**	**−0.180**	**0.101**	**−0.852**
	(−3.76)	(4.24)	(−1.86)	(4.22)	(3.07)	(−3.09)	(4.50)	(−2.60)
Accounting variables								
leverage ratio	0.091	0.051	**0.104**	**0.030**	0.618	0.081	**0.050**	−0.491
	(1.69)	(3.57)	(2.42)	(2.51)	(0.78)	(1.98)	(3.39)	(−1.67)
book-to-market ratio	0.030	−0.014	0.018	−0.007	0.227	0.033	−0.013	−0.033
	(1.10)	−(1.92)	(0.99)	(−1.17)	(0.24)	(1.27)	(−1.89)	(−0.30)
profitability	−0.080	0.011	−0.053	0.008	0.590	−0.068	0.013	0.145
	(−0.71)	(1.02)	(−0.77)	(0.79)	(0.51)	(−0.74)	(1.21)	(0.59)
Number of obs.	54	54	54	54	54	54	54	54
Adjusted R^2	0.171	0.582	0.110	0.338	0.071	0.138	0.590	0.225

Using cross-firm data within each credit category, we regress estimated barrier to price ratios, jump intensities, and barrier volatilities against the variables listed above. A White (1980) heteroscedasdicity-consistent covariance estimator is used to compute t-statistics, which appear in parentheses. A bold number indicates that the parameter estimate is statistically significant at the 1% level.

Table 8: Robustness of Parameter Estimates with Equity Volatility Estimated from Different Horizons

Constant Barrier Model

	A				BBB				BB			
	90 days		270 days		90 days		270 days		90 days		270 days	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	2.995	96.1%	2.061	97.4%	2.770	95.3%	2.077	96.2%	2.138	92.9%	1.965	91.1%
λ	0.004	97.4%	0.004	98.7%	0.010	98.1%	0.010	98.1%	0.037	100%	0.036	100%
$B/\overline{S}$	0.061		0.043		0.076		0.057		0.084		0.077	

Stochastic Barrier Model

	A				BBB				BB			
	90 days		270 days		90 days		270 days		90 days		270 days	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	0.988	91.0%	0.736	93.6%	1.642	94.3%	1.286	92.5%	2.018	94.6%	1.956	91.1%
σ_B	0.988	92.3%	1.041	94.9%	0.859	93.4%	0.901	90.6%	1.516	92.9%	1.404	96.4%
λ	0.002	83.3%	0.003	89.7%	0.005	69.8%	0.005	66.0%	0.020	76.8%	0.021	78.6%
$B/\overline{S}$	0.021		0.016		0.048		0.038		0.093		0.086	

Uncertain Barrier Model

	A				BBB				BB			
	90 days		270 days		90 days		270 days		90 days		270 days	
	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)	mean	sig.(1%)
B	2.071	75.6%	1.319	76.9%	1.863	72.6%	1.351	73.6%	1.498	60.7%	1.358	44.6%
σ_u	0.660	87.2%	0.725	89.7%	0.667	87.7%	0.708	84.0%	0.532	60.7%	0.541	57.1%
λ	0.004	97.4%	0.004	97.4%	0.009	98.1%	0.009	98.1%	0.035	96.4%	0.035	98.2%
$B/\overline{S}$	0.042		0.027		0.051		0.036		0.063		0.057	

This table reports the cross-firm average of parameter estimates from the constant barrier, stochastic barrier, and uncertain barrier models for each credit category with 90-day and 270-day time windows to compute the equity volatility for a firm. A Newey-West (1987) consistent covariance estimator with five lags is used to compute t-statistics, which are reported below parameter estimates in parentheses. The percentage of firms with a statistically significant (at the 1% level) parameter estimate is also reported for each credit rating category.

Table 9: In-Sample Fit with Different Volatility Estimates

Constant Barrier Model

	A						BBB						BB					
	90 days			270 days			90 days			270 days			90 days			270 days		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	5.8	7.6	0.21	5.8	7.5	0.32	18.4	24.6	0.25	17.9	23.2	0.37	68.4	89.9	0.33	63.4	81.8	0.42
CDS_{5y}	5.3	7.1	0.25	5.2	6.6	0.36	17.2	23.9	0.29	16.7	22.3	0.38	59.9	80.9	0.36	55.5	74.6	0.45

Stochastic Barrier Model

	A						BBB						BB					
	90 days			270 days			90 days			270 days			90 days			270 days		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	4.2	5.5	0.51	4.1	5.1	0.57	13.4	18.0	0.52	13.0	17.1	0.57	48.4	64.7	0.60	44.7	59.4	0.66
CDS_{5y}	4.6	5.9	0.44	4.6	5.8	0.47	14.5	19.5	0.44	14.3	18.9	0.47	46.6	62.0	0.57	43.5	57.9	0.62

Uncertain Barrier Model

	A						BBB						BB					
	90 days			270 days			90 days			270 days			90 days			270 days		
	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$	MAD	RMSE	$\overline{R}^2$
CDS_{3y}	4.9	6.3	0.39	4.7	5.9	0.47	15.7	21.0	0.43	15.4	19.8	0.49	65.0	88.4	0.40	61.4	83.0	0.48
CDS_{5y}	5.1	6.7	0.32	4.9	6.3	0.41	16.5	22.7	0.37	15.8	20.7	0.42	59.3	82.1	0.39	56.5	81.2	0.47

This table presents the in-sample fit of the constant barrier, stochastic barrier, and uncertain barrier models with 60-day and 90-day time windows to compute the equity volatility of a firm. The cross-firm average of the mean absolute deviation (MAD) and the root mean squared error (RSMSE) of in-sample pricing errors of 3-year and 5-year CDS premia for each credit rating category are reported. The reported numbers are in basis points. The average of R^2s of regressing observed 3-year and 5-year CDS premia on model-implied CDS premia for each credit rating category are also reported.