Pricing Credit Default Swaps with Option-Implied Volatility

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Abstract

Using the industry benchmark CreditGrades model to analyze credit default swap (CDS) spreads across a large number of firms, we demonstrate that the performance of the model can be significantly improved if one calibrates the model with option-implied volatility in lieu of historical volatility. Moreover, the advantage of option-implied volatility is greater among firms with more volatile CDS spreads, more actively traded options, and lower credit ratings. These results are robust both in- and out-of-sample, and are insensitive to historical volatilities estimated at short or long horizons.

1 Introduction

The credit derivatives market, especially that of credit default swaps, has grown exponentially during the past decade. Along with this new development comes the need to understand the pricing of credit default swaps. CDS contracts are often used by financial institutions to hedge against the credit risk in their loan portfolios. More recently, however, they have become popular in relative value trading strategies such as capital structure arbitrage (Currie and Morris, 2002). Consequently, a suitable pricing model has to reproduce both accurate CDS spreads and the relation between CDS spreads and the pricing of other corporate securities, such as common stocks, stock options, and corporate bonds.

In this article, we present an empirical study of CDS pricing using an industry benchmark model called CreditGrades. As explained in the CreditGrades Technical Document (2002), this model was jointly developed by Deutsche Bank, Goldman Sachs, JPMorgan, and the RiskMetrics Group as a standard of transparency in the credit market. Mostly based on the seminal Black and Cox (1976) model and extended to account for uncertain default thresholds, CreditGrades provides for simple closed-form formulas relating CDS pricing to the equity price and equity volatility. We examine the performance of the model across a large number of firms. We also estimate the parameters of the model using data from both equity and options markets, and incorporate the option-implied volatility into the calibration procedure.

The linkage between CDS and options markets can arise in several contexts. From a theoretical option pricing perspective, the option-implied volatility reflects the expected future volatility and the volatility risk premium, both of which have been shown to explain CDS valuation in a regression-based framework (Cao, Yu, and Zhong, 2010). From a market microstructure perspective, recent evidence points to the presence of informed trading in both the options market (Cao, Chen, and Griffin, 2005; Pan and Poteshman, 2006) and the CDS market (Acharya and Johnson, 2007). Theoretically, whether informed traders will exploit their information using derivatives is likely to be a function of the leverage and liquidity of the derivatives markets and the overall presence of information asymmetry (Black, 1975; Back, 1993; Easley, O'Hara, and Srinivas, 1998). Consequently, we expect the information content of option-implied volatility for CDS valuation to exhibit firm-level variations consistent with these predictions.

We begin our analysis by estimating the CreditGrades model for each of the 220 sample firms. Specifically, we minimize the sum of squared CDS pricing errors over three parameters of the model: the mean default threshold, the default threshold uncertainty, and the bond recovery rate. For the equity volatility input, we use either an option-implied volatility estimate or a backward-looking historical volatility. We then compute the ratio of the implied volatility-based pricing error to the historical volatility-based pricing error for each firm, and then link this ratio to firm-specific characteristics.

Overall, our results indicate that the use of option-implied volatility yields a better fit of the model to market CDS spreads during the sample period of 2001-04. To examine how this improvement of model performance varies at the firm-level, we regress the pricing error ratio on a number of firm-level characteristics. In particular, we include the option trading volume and open interest as measures of options market liquidity, along with the volatility of the CDS spread and credit rating as proxies of the amount of informed trading in the marketplace. We find that the ratio of the pricing errors is smaller (the advantage of implied volatility over historical volatility is greater) among firms with more volatile CDS spreads and actively traded options, as well as lower rated firms. Hence, our results are broadly consistent with the predictions of market microstructure theories.

We conduct several robustness checks. First, we use a rolling-window estimation approach to improve the performance of model-fitting. For each day in our sample period, we use only the previous 22, 126, or 252 observations to estimate the parameters of the CreditGrades model and generate a one-day-ahead forecast of the CDS spread. The rolling-window estimation generally yields lower pricing error, and most importantly, the advantage of implied volatility over historical volatility remains. Second, we repeat the pricing analysis with the 22-, 63-, 126-, and 1,000-day historical volatilities. We find that the historical volatility-based CDS pricing errors follow an inverse U-shaped pattern with respect to the horizon of the historical volatility estimator. Namely, the historical volatility-based pricing error increases as the estimation horizon is either shortened or lengthened. Nevertheless, the cross-sectional behavior of the ratio of pricing errors remains unchanged in all cases. These results suggest that the information advantage of implied volatility over historical volatility is robust to the length of data used in the estimation of the CreditGrades model and the calculation of historical volatility.

There is a significant literature on the relation between CDS pricing and equity volatility. For example, Campbell and Taksler (2003), Ericsson, Jacobs, and Oviedo-Helfenberger (2007), and Zhang, Zhou, and Zhu (2008) have analyzed the connection between CDS spreads and equity historical volatilities. Our paper differs from these studies due to its focus on the option-implied volatility. Cremers, Driessen, Maenhout, and Weinbaum (2006) estimate a panel regression of corporate bond yield spreads and options market variables. Cao, Yu, and Zhong (2010) estimate firm-level time-series regressions of credit spreads and focus on the role of the volatility risk premium in explaining CDS pricing. In comparison, we address the inherently nonlinear relation between CDS spreads and equity volatility by fitting a structural credit risk model. In addition, we concentrate on the cross-sectional interpretation of the firm-level CDS pricing errors. Finally, our paper is similar in spirit to Stamicar and Finger (2006), who use case studies to illustrate the calibration of the CreditGrades model with options data. Our analysis is more in-depth and broader in scope with a significantly larger sample.

The rest of this paper is organized as follows: In Section 2, we present the data and summary statistics. In Section 3, we discuss the CreditGrades model. Section 4 explains our estimation procedure and overall results. The cross-sectional analysis of pricing errors is presented in Section 5. Further robustness checks can be found in Section 6. We conclude with Section 7.

2 Data

The sources of the variables used in our study are documented as follows:

- *Credit Default Swaps.* We obtain single-name CDS spreads from the Markit Group. According to Markit, it receives contributed CDS data from market makers based on their official books and records. The data then undergoes a rigorous cleaning process to test for staleness, outliers, and inconsistency. Any contribution that fails any one of these tests will be rejected. The full term structures of CDS spreads and recovery rates are available by entity, tier, currency, and restructuring clause. In this paper, we use the composite spreads of US dollar-denominated five-year CDS contracts written on senior unsecured debt of North American obligors. Furthermore, we limit ourselves to CDS contracts that allow for so-called "modified restructuring," which restricts the range of maturities of debt instruments that can be delivered in a credit event.

- *Equity Options.* We collect options data from OptionMetrics, which provides daily closing prices, open interest, and trading volume on exchange-listed equity options in the United States. We do not use the standardized implied volatility provided by OptionMetrics, since this measure can be noisy due to the small number of contracts used in OptionMetrics' interpolation process. Instead, we use the binomial model for American options with discrete dividend adjustments to estimate the level of implied volatility that would minimize the sum-of-squared pricing errors across all put options with non-zero open interests.

- *Other Variables.* We collect daily stock returns, equity prices, and common shares outstanding from CRSP, and the book value of total liabilities and total assets from Computstat. Historical volatility measures with different estimation horizons, ranging from 22, 63, 126, 252, to 1,000 trading days are calculated using the stock returns. Leverage ratio is defined as total liabilities divided by the sum of total liabilities and market capitalization.

We exclude firms in the financial, utility, and government sectors, and we further require that each firm must have at least 377 observations of the CDS spread, the implied volatility, the 252-day historical volatility, and the leverage ratio. The final sample consists of 220 firms in the sample period of 2001-2004. The cross-sectional summary statistics of the time-series means of the variables are presented in Table 1. The mean CDS spread is 152bp and the cross-sectional standard deviation is 216bp. The average firm also has an implied volatility of 38.80 percent, a 252-day historical volatility of 40.43 percent, and a leverage ratio of 45.80%. Finally, the average firm has a market capitalization slightly in excess of \$20 billion, which is similar to the size of a typical S&P 500 company.

3 The CreditGrades Model

To effectively address the nonlinear dependence of the CDS spread on its determinants, we conduct a pricing analysis using a structural credit risk model with equity volatility calculated using information from either the options market or the stock market. Specifically, we use the CreditGrades model, an industry benchmark model jointly developed by RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank that is based on the structural model of Black and Cox (1976). Detailed documentation of this model can be found in the CreditGrades Technical Document (2002), a summary of which is given below. Although a full menu of structural models have been developed following the seminal work of Merton (1974), we choose this industry model for three reasons. First, it appears to be widely used by practitioners (Currie and Morris (2002)). Second, it contains an element of uncertain recovery rates, which helps to generate realistic short-term credit spreads. Third, the model yields a simple analytic CDS pricing formula. We are aware of the general concern of model misspecification when choosing to work with any particular model. Our methodology, however, is applicable to other structural models in a straightforward manner, which we leave to future research.

The CreditGrades model assumes that under the pricing measure, the firm's value per equity share is given by

$$\frac{dV_t}{V_t} = \sigma dW_t, \tag{1}$$

where W_t is a standard Brownian motion and σ is the asset volatility. The firm's debt per share is a constant D and the (uncertain) default threshold as a percentage of debt per share is

$$L = \overline{L} e^{\lambda Z - \lambda^2/2}, \tag{2}$$

where $\overline{L} = E(L)$ is the expected value of the default threshold, Z is a standard normal random variable, and $\lambda^2 = var(\ln L)$ measures the uncertainty in the default threshold value. Note that the firm value process is assumed to have zero drift. This assumption is consistent with the observation that leverage ratios tend to be stationary over time.

Default is defined as the first passage of V_t to the default threshold LD. The density of the default time can be obtained by integrating the first passage time density of a geometric Brownian motion to a fixed boundary over the distribution of L. However, CreditGrades provides an approximate solution to the survival probability $q(t)$ using a time-shifted Brownian motion, yielding the following result:[1]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{3}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function, and

$$\begin{aligned} d &= \frac{V_0}{\overline{L}D} e^{\lambda^2}, \\ A_t &= \sqrt{\sigma^2 t + \lambda^2}. \end{aligned}$$

With constant interest rate r, bond recovery rate R, and the survival probability function $q(t)$, it can be shown that the CDS spread for maturity T is

$$c = -\frac{(1-R)\int_0^T e^{-rs} dq(s)}{\int_0^T e^{-rs} q(s)\, ds}. \tag{4}$$

[1] The approximation assumes that W_t starts not at $t = 0$, but from an earlier time. In essence, the uncertainty in the default threshold is shifted to the starting value of the Brownian motion.

Substituting $q(t)$ into the above equation, the CDS spread for maturity T is given by

$$c(0,T) = r(1-R)\frac{1-q(0)+H(T)}{q(0)-q(T)e^{-rT}-H(T)}, \tag{5}$$

where

$$\begin{aligned}
H(T) &= e^{r\xi}\left(G(T+\xi)-G(\xi)\right), \\
G(T) &= d^{z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}}-z\sigma\sqrt{T}\right)+d^{-z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}}+z\sigma\sqrt{T}\right), \\
\xi &= \lambda^2/\sigma^2, \\
z &= \sqrt{1/4+2r/\sigma^2}.
\end{aligned}$$

Note that equation (5) depends on the asset volatility σ, which is unobserved. Stamicar and Finger (2006) derive an analytic pricing formula for equity options within the above framework, which can be used to infer the asset volatility from the market prices of equity options. Moreover, they show that a local approximation to the volatility surface,

$$\sigma = \sigma_S\frac{S}{S+\overline{L}D}, \tag{6}$$

in which σ_S is taken to be the implied volatility from equity options, also produces accurate CDS spreads.

4 Estimation Procedures and Results

To begin the pricing analysis, we note that the CreditGrades model requires the following eight inputs to generate a CDS spread: the equity price S, the debt per share D, the interest rate r, the average default threshold $\overline{L}$, the default threshold uncertainty λ, the bond recovery rate R, the time to expiration T, and finally the equity volatility σ_S, which we take as either a historical volatility or an option-implied volatility. Hence, the CreditGrades pricing formula can be abbreviated as

$$CDS_t = f\left(S_t, D_t, r_t, \sigma_t, T-t; \overline{L}, \lambda, R\right), \tag{7}$$

recognizing that three of the parameters ($\overline{L}$, λ, and R) are unobserved. To conduct the pricing analysis, we take the entire sample period for each firm (say, of length N) to estimate these three parameters. Specifically, let CDS_i and $\widehat{CDS}_i$ denote the observed and model CDS spreads on day i for a given firm. We minimize the sum-of-squared relative pricing errors:

$$SSE = \min_{\overline{L},\lambda,R} \sum_{i=1}^{N} \left(\frac{\widehat{CDS}_i - CDS_i}{CDS_i} \right)^2 . \tag{8}$$

Table 2 present the estimated parameters and the pricing errors. Across the 220 firms, the average parameters are similar for both implied volatility-based and historical volatility-based estimation. In the latter case, the average default threshold is $\overline{L} = 0.62$, the default threshold uncertainty is $\lambda = 0.39$, and the bond recovery rate is $R = 0.58$. In comparison, the CreditGrades Technical Document (2002) assumes $\overline{L} = 0.5$, $\lambda = 0.3$, and takes the bond recovery rate R from a proprietary database from JPMorgan. These values are reasonably close to the cross-sectional average parameter estimates presented above.

Table 2 also presents the cross-sectional average of the average pricing error, the average absolute pricing error, and the root-mean-squared pricing error (RMSE) based on CDS spread levels as well as percentage deviations from observed levels.[2] Generally, the estimation based on implied volatility yields smaller fitting errors. For instance, the implied volatility-based RMSE is 59.73bp, while the historical volatility-based counterpart is 79.59bp. When examining average pricing errors, we find that the implied volatility-based and historical volatility-based pricing errors are -15.24bp and -25.21bp, respectively. Similarly, the implied volatility-based percentage RMSE is 0.46, while the historical volatility-based percentage RMSE is 0.50.

To check if the pricing errors vary among different groups of firms, we partition the sample firms into three groups according to their sample CDS spread volatility. Table 3 present the results. We observe that the implied volatility yields significantly smaller pricing

[2] Note that it is the sum of squared relative pricing errors that we minimize to obtain the estimated model parameters. We have also examined results when we minimize the pricing errors measured in CDS spread levels. We find that the results are qualitatively similar.

errors among the most volatile group of firms. This finding motivates us to investigate the cross-sectional difference of pricing errors in the next section.

5 Pricing Error Ratio Analysis

To examine the balance between historical and implied volatility-based pricing errors, we construct a pricing error ratio (Ratio_RMSE), which is equal to the implied volatility-based percentage RMSE divided by the historical volatility-based percentage RMSE. Table 4 presents the summary statistics of the pricing error ratio. This ratio varies substantially in the cross-section, with a median value of 0.95. This observation suggests that while implied volatility yields smaller pricing errors than historical volatility across our entire sample, a subset of the firms might enjoy significantly smaller pricing errors when implied volatility is used in lieu of historical volatility in model calibration. Therefore, in the next step, we conduct cross-sectional regressions with Ratio_RMSE as the dependent variable and investigate whether certain firm-level characteristics are related to this ratio.

When choosing the appropriate firm-level characteristics, we are motivated by recent studies that examine the role of option and CDS market information in forecasting future stock returns. For example, Acharya and Johnson (2007) suggest that the incremental information revelation in the CDS market relative to the stock market is driven by banks that trade on their private information. Cao, Chen, and Griffin (2005) show that call option volume and next-day stock returns are strongly correlated prior to takeover announcements, but are unrelated during "normal" sample periods. Pan and Poteshman (2006) find a predictive relation between option volume and future stock returns that becomes stronger when there is a larger presence of informed trading. To the extent that heightened volatility in the CDS market is an indication of informed trading, option-implied volatility can be especially useful in explaining the CDS spread for more volatile firms. We therefore include CDS spread volatility as one of our explanatory variables.

A related question is whether the information content of implied volatility for CDS spreads varies across firms with different credit ratings. Among the sample firms, we observe a broad spectrum of credit quality, ranging from AAA (investment-grade) to CCC (speculative-grade). We note that information asymmetry is expected to be larger for lower-rated firms. Banks and other informed traders/insiders are likely to explore their information advantage in both the CDS and options markets among these firms, not higher-rated firms with fewer credit risk problems. We therefore include credit rating as another explanatory variable.

Finally, We also include option volume and open interest in the analysis. While it has been argued that informed investors prefer to trade options because of their inherent leverage, the success of their strategy depends on sufficient market liquidity. To the extent that market illiquidity or trading cost constitutes a barrier to entry, we expect the signal-to-noise ratio of implied volatility to be higher for firms with better options market liquidity. Specifically, we normalize option volume by stock volume and open interest by the total common shares outstanding for each firm and each day in the sample period. We normalize option volume and open interest so that the comparison across firms is meaningful. We use option open interest in addition to option volume because it does not suffer from the double counting of offsetting transactions.

Table 4 presents the summary statistics of the regression variables. We note that the sample firms are mostly large investment-grade firms with a median rating of BBB.[3] The CDS spread volatility has a large positive skew—its mean is higher than the third quartile, and its standard deviation is more than three times its mean. This indicates that some firms have extremely volatile CDS spreads.

In Table 5, we present the pricing error ratio regression results, and find that Ratio_RMSE to be smaller for firms with lower ratings and higher CDS spread volatilities. Additionally, total assets is significant with a negative sign, the option open interest is marginally significant with a negative sign, and the option-to-stock volume ratio appears to be

[3] To convert the credit rating into a numerical grade, we use the following convention: 1-AAA, 2-AA, 3-A, 4-BBB, 5-BB, 6-B, and 7-CCC.

insignificant. To put these coefficients (in Regression Three) into perspective, consider the median value of Ratio_RMSE at 0.95. A one-standard-deviation increase in the CDS spread volatility would lower it to 0.88. A one-standard-deviation increase in the option open interest would lower it further to 0.80. Lower the credit rating by one standard deviation reduces Ratio_RMSE still to 0.70. It appears that for firms with higher CDS spread volatilities, higher option open interests, and lower credit ratings, the implied volatility is especially informative for explaining CDS spreads, resulting in substantially smaller structural model pricing errors relative to when historical volatility is used in the same calibration.

6 Robustness Checks

6.1 Rolling-Window Out-of-Sample Estimation

Having demonstrated that using option-implied volatility can significantly improve the performance of the CreditGrades model in in-sample tests, we now turn to an out-of-sample pricing analysis. In this exercise, we attempt to capture what an investor will experience if he/she uses the implied volatility or historical volatility to forecast the CDS spread. Specifically, for each day t in the sample period, we use a rolling-window (of the past 252 observations) to recalibrate the model following the estimation method outlined in Section 4.[4] We then use the recalibrated parameters and the day $t-1$ inputs to compute a CDS spread for day t. This allows us to calculate implied volatility- or historical volatility-based out-of-sample pricing errors.

Table 6 presents our findings. Compared to the results in Table 2, the rolling-window estimation improves the overall fitting of the CreditGrade model for the case of implied volatility. For example, the RMSE decreases from 59.73bp to 49.30bp, and the percentage RMSE decreases from 0.46 to 0.43. Interestingly, while the RMSE for the case of historical volatility also decreases from 79.59bp to 63.59bp, the percentage RMSE for historical volatility actually increases from 0.50 to 0.54. If anything, the advantage of implied volatility over

[4] We have also used 22-day and 126-day rolling windows to implement this test and found that our main results remain unchanged. To conserve space, these results are not reported, but are available upon request.

historical volatility is even greater in the out-of-sample exercise. Moreover, a cross-sectional analysis using the ratio of these pricing errors, presented in Table 7, produces results similar to those of our in-sample pricing error analysis. Namely, the ratio of out-of-sample percentage RMSE is smaller (i.e. the advantage of implied volatility over historical volatility is larger) for firms with more volatile CDS spreads, larger option open interests, and lower credit ratings.

6.2 Historical Volatilities with Alternative Horizons

So far, we have compared the information content of implied volatility to that of the 252-day historical volatility in predicting CDS spreads. In this section, we present evidence on historical volatilities with other estimation horizons. Especially, we want to consider both the ability of long-dated estimators to produce stable asset volatility measures, and the advantage of short-dated estimators to timely adjust to new market information. Therefore, we repeat the pricing exercise of the preceding section with different historical volatility estimators (ranging from 22-day to 1000-day). The results are presented in Table 8. When pricing errors are measured in levels, we see that implied volatility produces the smallest average pricing errors among all estimators used. Compared to the smallest RMSE among all historical volatility estimators at 72.90bp for the 1,000-day historical volatility, the RMSE for implied volatility is 18 percent smaller, at 59.73bp. When we compare percentage pricing errors, the 1,000-day historical volatility produces the smallest RMSE. In this case, the slight advantage of the 1,000-day historical volatility over implied volatility can be attributed to its ability to fit smooth and low levels of the CDS spread.[5]

When we conduct the cross-sectional pricing error ratio analysis in Table 9, we find that the results closely resemble those in Table 5. Namely, the Ratio RMSE variable is lower with higher CDS spread volatility, higher option open interest, and lower credit rating. Therefore,

[5] To see the logic behind this argument, assume that the observed spread is 200bp. A fitted spread of 500bp yields a relative pricing error of 150 percent. When the observed spread is 500bp, a fitted spread of 200bp yields a relative pricing error of -60 percent. Therefore, the relative pricing error measure tends to reward model specifications that provide a better fit to spreads when they are low.

even as the pricing performance varies among the different historical volatility inputs used in the calibration, implied volatility continues to be more informative among the same subset of firms identified by our earlier analysis. Overall, these additional robust checks confirm that the information advantage of implied volatility is robust to historical volatility estimators of different horizons.

7 Conclusion

Can we use information from the options market to better price credit derivatives? How does the performance of CDS pricing using option-implied volatility vary with the degree of information asymmetry and market frictions? Using a large sample of firms with both CDS and options data available, we find that option-implied volatility dominates historical volatility in fitting CDS spreads to the CreditGrades model. Moreover, we find that the need to use option-implied volatility is more imperative when there is a large presence of informed/insider trading and when the options market is more liquid. Additional robustness checks confirm that our findings are robust to a rolling-window estimation approach and historical volatilities estimated with different horizons.

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Table 1. Summary Statistics

Cross-sectional summary statistics of the time-series means for 220 sample firms. CDS Spread is the daily five-year composite credit default swap spread; Historical Volatility is the 252-day historical volatility; Implied Volatility is the volatility inferred from put options with non-zero open interests; Market Capitalization is the product of the stock price and shares outstanding; Leverage is the ratio of total liability over the sum of total liability and market capitalization. The sample period extends from January 2001 through June 2004.

	Mean	Q1	Median	Q3	Standard Deviation
CDS Spread (basis point)	152.40	48.63	82.77	175.24	215.66
Historical Volatility (%)	40.43	32.41	36.94	44.99	12.90
Implied Volatility (%)	38.80	32.51	36.61	42.81	9.68
Market Capitalization ($billion)	20.88	3.54	9.22	19.04	37.30
Leverage Ratio (%)	45.80	33.70	46.89	59.65	19.40

Table 2. Estimated Parameters and Pricing Errors

Cross-sectional averages and standard errors of estimated parameters and pricing errors. The CreditGrades model is estimated for each firm where either option-implied volatility or 252-day historical volatility is used as an input. Then the estimated parameters and pricing errors are averaged across 220 sample firms. $\bar{L}$ is the expected default threshold; λ is the default threshold uncertainty; R is the recovery rate. For pricing errors (or percentage pricing errors), we report the average pricing error, average absolute pricing error, and root-mean-squared-errors (RMSE).

	Implied Volatility		Historical Volatility	
	Mean	Standard Error	Mean	Standard Error
Estimated Parameters				
$\bar{L}$	0.69	0.03	0.62	0.04
λ	0.39	0.01	0.39	0.01
R	0.58	0.01	0.58	0.01
Pricing Errors (in basis points)				
Average Pricing Error	-15.24	2.05	-25.21	3.73
Average Absolute Pricing Error	42.62	2.78	56.67	4.97
RMSE	59.73	5.11	79.59	8.96
Percentage Pricing Errors				
Average Pricing Error	-0.15	0.01	-0.20	0.01
Average Absolute Pricing Error	0.39	0.01	0.43	0.01
RMSE	0.46	0.01	0.50	0.01

Table 3. Pricing Errors Partitioned by CDS Volatility

Cross-sectional averages of pricing errors partitioned by CDS volatility. The CreditGrades model is estimated for each firm where either option-implied volatility or 252-day historical volatility is used as an input. Then the pricing errors are averaged across sample firms in each sub-group. For pricing errors (or percentage pricing errors), we report the average pricing error, average absolute pricing error, and root-mean-squared-errors (RMSE).

	Group1 (Least volatile)		Group2		Group3 (Most volatile)	
	I.V.	Hist. Vol.	I.V.	Hist. Vol.	I.V.	Hist. Vol.
Pricing Errors (in basis points)						
Average Pricing Error	-6.44	-8.96	-6.45	-13.77	-32.95	-53.05
Average Absolute Pricing Error	19.45	18.50	32.53	31.54	76.04	120.30
RMSE	24.14	21.55	42.79	39.21	112.50	178.54
Percentage Pricing Errors						
Average Pricing Error	-0.22	-0.25	-0.14	-0.19	-0.08	-0.15
Average Absolute Pricing Error	0.48	0.47	0.42	0.43	0.27	0.40
RMSE	0.56	0.54	0.50	0.49	0.33	0.48

Table 4. Properties of Cross-Sectional Regression Variables

Summary statistics of the cross-sectional regression variables for 220 sample firms. Ratio_RMSE is the ratio of the RMSEs (percentage pricing errors) between using implied volatility and 252-day historical volatility. CDS Spread Volatility is the volatility of the CDS spread across the sample period in basis points. Option Volume (standardized by stock volume), Option Open Interest (standardized by total shares outstanding), Leverage Ratio, Total Assets, and Rating are time-series means of the respective daily variables. To convert the credit rating into a numerical grade, we use the following convention: 1-AAA, 2-AA, 3-A, 4-BBB, 5-BB, 6-B, and 7-CCC. Correlation coefficients with p-values less than 0.05 are marked with an asterisk.

	Mean	Q1	Median	Q3	Standard Deviation
Ratio_RMSE	0.97	0.78	0.95	1.13	0.33
CDS Spread Volatility	103.66	18.59	36.22	90.09	368.00
Option Volume	0.09	0.03	0.07	0.12	0.07
Option Open Interest	0.02	0.01	0.01	0.03	0.02
Leverage Ratio	0.46	0.34	0.47	0.60	0.19
Total Assets ($billion)	23.63	5.16	11.23	24.36	52.17
Rating	3.84	3.00	4.00	4.00	0.95

Table 5. Cross-Sectional Regression Analysis of Structural Model Pricing Errors

Coefficients, *t* statistics (in parentheses), and adjusted *R*-squares of cross-sectional regressions for 220 sample firms. The dependent variable is Ratio_RMSE, the ratio of the RMSEs (percentage pricing errors) between using implied volatility and 252-day historical volatility. CDS Spread Volatility is the volatility of the CDS spread across the sample period in basis points. Option Volume (standardized by stock volume), Option Open Interest (standardized by total shares outstanding), Leverage Ratio, Total Assets, and Rating are time-series means of the respective daily variables.

	1	2	3
Intercept	1.46***	1.39***	1.37***
	(13.88)	(14.04)	(11.82)
CDS Spread Volatility (/100)	-0.01**	-0.02**	-0.02**
	(-2.42)	(-2.54)	(-2.56)
Option Volume	-0.48		0.21
	(-1.41)		(0.42)
Option Open Interest		-3.32**	-3.93*
		(-2.38)	(-1.95)
Leverage	0.18	0.20	0.22
	(1.33)	(1.53)	(1.58)
Total Assets (/100)	-0.11**	-0.12**	-0.12**
	(-2.24)	(-2.39)	(-2.40)
Rating	-0.13***	-0.11***	-0.11***
	(-4.35)	(-3.50)	(-3.28)
Adjusted R^2	15%	16%	16%

***,**,* represent the significance level of 1%, 5%, and 10% respectively.

Table 6. Properties of Estimated Parameters and Out-of-sample Pricing Errors using a 252-day Rolling Window

This table reports the cross-sectional averages and standard errors of the estimated parameters and one-day-ahead out-of-sample forecasting (pricing) errors for 220 sample firms. The CreditGrades model is estimated for each firm where either option-implied volatility or 252-day historical volatility is used as an input. For each day, the rolling estimation window is the previous 252 trading days. $\bar{L}$ is expected default threshold; λ default threshold uncertainty; R recovery rate. The one-day-ahead out-of-sample forecast is then calculated by using the estimated parameters and the last day's inputs. For pricing errors (or percentage pricing errors), we report the average pricing error, the average absolute pricing error and the root-mean-squared-errors (RMSE).

	Implied Volatility		Historical Volatility	
	Mean	Standard Error	Mean	Standard Error
Estimated Parameters				
$\bar{L}$	0.74	0.03	0.64	0.03
λ	0.40	0.01	0.39	0.01
R	0.58	0.00	0.56	0.01
Pricing Errors (in basis points)				
Average Pricing Error	-12.80	2.71	-9.95	3.16
Average Absolute Pricing Error	35.72	3.42	49.40	4.85
RMSE	49.30	5.79	63.59	7.39
Percentage Pricing Errors				
Average Pricing Error	-0.20	0.01	-0.22	0.02
Average Absolute Pricing Error	0.37	0.01	0.48	0.01
RMSE	0.43	0.01	0.54	0.01

Table 7. Cross-sectional Regression Analysis of Structural Model: Out-of-sample Pricing Errors using a 252-day Rolling Window

Coefficients, *t* statistics (in parentheses), and adjusted *R*-squares of cross-sectional regressions for 220 sample firms. For each day, the rolling estimation window is the previous 252 trading days. The one-day-ahead out-of-sample forecast is then calculated by using the estimated parameters and the last day's inputs. The dependent variable is Ratio_RMSE_Out, the ratio of the out-of-sample RMSEs (percentage pricing errors) between using implied volatility and 252-day historical volatility. CDS Spread Volatility is the volatility of the CDS spread across the sample period in basis points. Option Volume (standardized by stock volume), Option Open Interest (standardized by total shares outstanding), Leverage Ratio, Total Assets, and Rating are time-series means of the respective daily variables.

	1	2	3
Intercept	1.13***	1.08***	1.05***
	(11.41)	(11.56)	(9.70)
CDS Spread Volatility (/100)	-0.01**	-0.01**	-0.01**
	(-2.23)	(-2.33)	(-2.35)
Option Volume	-0.33		0.23
	(-1.04)		(0.50)
Option Open Interest		-2.38*	-3.02*
		(-1.93)	(-1.69)
Leverage	0.16	0.17	0.19
	(1.22)	(1.37)	(1.46)
Total Assets (/100)	-0.14***	-0.14***	-0.15***
	(-2.90)	(-3.06)	(-3.06)
Rating	-0.08***	-0.06**	-0.06*
	(-2.70)	(-2.08)	(-1.91)
Adjusted R^2	9%	10%	10%

***,**,* represent the significance level of 1%, 5%, and 10% respectively.

Table 8. Estimated Parameters and Pricing Errors using Historical Volatilities of Alternative Horizons

This table reports the cross-sectional averages of estimated parameters and pricing errors. The CreditGrades model is estimated for each firm where either option-implied volatility or historical volatility (of alternative horizon) is used as an input. Then the estimated parameters and pricing errors are averaged across 220 sample firms. $\bar{L}$ is the expected default threshold; λ is the default threshold uncertainty; R is the recovery rate. For pricing errors (or percentage pricing errors), we report the average pricing error, the average absolute pricing error and the root-mean-squared-errors (RMSE).

	Historical Volatility					Implied Volatility
	22-day	63-day	126-day	252-day	1000-day	
Estimated Parameters						
$\bar{L}$	0.44	0.60	0.67	0.62	0.45	0.69
λ	0.46	0.44	0.41	0.39	0.29	0.39
R	0.57	0.58	0.56	0.58	0.46	0.58
Pricing Errors (in basis points)						
Average Pricing Error	-35.98	-18.15	-17.11	-25.21	-35.24	-15.24
Average Absolute Pricing Error	78.50	60.03	54.82	56.67	51.07	42.62
RMSE	108.78	82.73	74.06	79.59	72.90	59.73
Percentage Pricing Errors						
Average Pricing Error	-0.42	-0.25	-0.21	-0.20	-0.13	-0.15
Average Absolute Pricing Error	0.67	0.52	0.47	0.43	0.31	0.39
RMSE	0.76	0.59	0.54	0.50	0.36	0.46

Table 9. Cross-Sectional Regression Analysis of Structural Model Pricing Errors using Historical volatilities of Alternative Horizons

Coefficients, *t* statistics (in parentheses), and adjusted *R*-squares of cross-sectional regressions using historical volatility of alternative horizons for 220 sample firms. The dependent variable is Ratio_RMSE, the ratio of the RMSEs (percentage pricing errors) between using implied volatility and historical volatility (of alternative horizon). CDS Spread Volatility is the volatility of the CDS spread across the sample period in basis points. Option Volume (standardized by stock volume), Option Open Interest (standardized by total shares outstanding), Leverage Ratio, Total Assets, and Rating are time-series means of the respective daily variables.

	Historical Volatility				
	22-day	63-day	126-day	252-day	1000-day
Intercept	0.74***	0.86***	1.00***	1.37***	2.07***
	(9.70)	(9.39)	(9.89)	(11.82)	(9.95)
CDS Spread Volatility (/100)	-0.01**	-0.01***	-0.01***	-0.02**	-0.02*
	(-2.31)	(-2.79)	(-2.77)	(-2.56)	(-1.75)
Option Volume	0.17	0.41	0.74*	0.21	1.49*
	(0.54)	(1.04)	(1.72)	(0.42)	(1.76)
Option Open Interest	0.60	-0.66	-2.37	-3.93*	-7.10**
	(0.45)	(-0.41)	(-1.34)	(-1.95)	(-2.29)
Leverage	0.18*	0.36***	0.41***	0.22	0.04
	(1.96)	(3.29)	(3.36)	(1.58)	(0.17)
Total Assets (/100)	-0.07*	-0.08**	-0.14***	-0.12**	-0.14*
	(-1.93)	(-2.01)	(-3.09)	(-2.40)	(-1.68)
Rating	-0.05**	-0.05*	-0.07**	-0.11***	-0.17***
	(-2.24)	(-1.95)	(-2.30)	(-3.28)	(-2.93)
Adjusted R^2	5%	7%	10%	16%	16%

***,**,* represent the significance level of 1%, 5%, and 10% respectively.