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Pricing Credit Default Swaps with Option-Implied Volatility

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Using the industry benchmark CreditGrades model to analyze credit default swap (CDS) spreads across a large number of companies during the 2007–09 credit crisis, the authors demonstrate that the performance of the model can be significantly improved by calibrating it with option-implied volatility rather than with historical volatility. Moreover, the advantage of using option-implied volatility is greater among companies with more volatile CDS spreads, more actively traded options, and lower credit ratings.

The credit derivatives market has grown exponentially over the past decade, especially for credit default swaps (CDSs). This development has brought with it the need to understand the pricing of CDSs. Financial institutions often use CDS contracts to hedge against the credit risk in their loan portfolios. More recently, CDS contracts have become popular in relative value trading strategies, such as capital structure arbitrage (Currie and Morris 2002). Consequently, a suitable pricing model must reproduce both accurate CDS spreads and the relationship between CDS spreads and the pricing of other corporate securities, such as common stocks, stock options, and corporate bonds.

Using an industry benchmark model called CreditGrades, we conducted an empirical study of CDS pricing. As explained in Finger (2002), the CreditGrades model was jointly developed by Deutsche Bank, Goldman Sachs, J.P. Morgan, and the RiskMetrics Group as a standard of transparency in the credit market. Based mostly on the seminal Black and Cox (1976) model and extended to account for uncertain default thresholds, the CreditGrades model provides simple, closed-form formulas that relate CDS pricing to the equity price and equity volatility. We examined the performance of the model across a large number of companies. More importantly, using data from both equity and options markets, we estimated the parameters of the model by incorporating the option-implied volatility into the calibration procedure.

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The link between CDSs and the options market 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 by using derivatives is likely to be a function of the leverage and liquidity of the derivatives market and the overall presence of informational asymmetry (Black 1975; Back 1993; Easley, O'Hara, and Srinivas 1998). Thus, one would expect the information content of option-implied volatility for CDS valuation to exhibit company-level variations consistent with these predictions.

The literature is replete with research on the relationship between CDS pricing and equity volatility. For example, several researchers have analyzed the connection between CDS spreads and historical equity volatilities (see Campbell and Taksler 2003; Ericsson, Jacobs, and Oviedo 2009; Zhang, Zhou, and Zhu 2009). Our study's focus on option-implied volatility differs from the focus of those studies. Cremers, Driessen, Maenhout, and Weinbaum (2008) estimated a panel regression of corporate bond yield spreads and options market variables. Cao, Yu, and Zhong (2010) estimated company-level time-series regressions of credit spreads and focused on the role of the volatility risk premium in explaining CDS pricing. In our study, we addressed the inherently nonlinear relationship between CDS spreads and equity volatility by fitting a structural credit risk model. Moreover, we concentrated on the cross-sectional interpretation of company-level CDS pricing errors. Although our study is similar in spirit to Stamicar and Finger (2006), who used case studies to illustrate the calibration of the CreditGrades model with options data, our analysis is both deeper and broader in scope, with a significantly larger sample of companies and a longer sample period that includes the recent credit crisis.[1] A supportive study by Luo (2008) showed that an extension of Yu's analysis (2006) of capital structure arbitrage to incorporate options market information significantly increases the Sharpe ratio of this popular hedge fund strategy.

Data and Summary Statistics

We obtained the data on the variables that we used in our study from various sources.

- *Credit default swaps*. We collected data on single-name CDS spreads from the Markit Group. According to Markit, market makers send it CDS data based on their official books and records. The data then undergo a rigorous cleaning process to test for staleness, outliers, and inconsistency. Any submitted data that fail any one of these tests are rejected. The full-term structures of CDS spreads and recovery rates are available by entity, tier, currency, and restructuring clause. In our study, we used the composite spreads of U.S.-dollar-denominated five-year CDS contracts written on senior unsecured debt of North American obligors. Furthermore, we limited our sample to CDS contracts that allow for so-called modified restructuring, which restricts the range of maturities of debt instruments that can be delivered during a credit event.
- *Equity options*. We obtained options data from OptionMetrics, which provides daily closing prices, open interest, and trading volume on exchange-listed equity options in the United States. We did not use the standardized implied volatility provided by OptionMetrics because that measure can be noisy owing to the small number of contracts used in OptionMetrics' interpolation process. Instead, we used the binomial model for U.S. 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 nonzero open interest.
- *Other variables*. From CRSP we collected data on daily stock returns, equity prices, and common shares outstanding. We obtained data on the book value of total liabilities and total assets from Compustat. Using stock returns, we calculated historical volatility measures with estimation horizons of 22, 63, 126, 252, and 1,000 trading days. We defined the leverage ratio as total liabilities divided by the sum of total liabilities and market capitalization.

We excluded companies in the financial, utility, and government sectors. We required that each company have at least 377 observations (about 18 months of daily observations) of the CDS spread, the implied volatility, the 252-day historical volatility, and the leverage ratio and that each company have no more than 5 percent of missing observations between the first and last dates of its coverage. Our final sample consisted of 332 companies over January 2007–October 2009. **Table 1** reports the cross-sectional summary statistics of the time-series means of the variables. The mean CDS spread was 198.30 bps, and the cross-sectional standard deviation was 243.94 bps. The average company had an implied volatility of 44.37 percent, a 252-day historical volatility of 43.38 percent, and a leverage ratio of 43.57 percent. Finally, the average company had a market capitalization of $20.61 billion, about the size of a typical S&P 500 Index company.

Table 1. Summary Statistics, January 2007–October 2009

	Mean	Q1	Median	Q3	Standard Deviation
CDS spread (bps)	198.30	57.02	110.52	225.22	243.94
Historical volatility (%)	43.38	33.47	40.47	51.55	14.14
Implied volatility (%)	44.37	35.28	42.32	49.48	12.81
Market cap ($ billions)	20.61	3.50	8.78	20.84	39.68
Leverage ratio (%)	43.57	30.78	44.10	54.41	16.49

Notes: This table presents cross-sectional summary statistics of the time-series means for 332 sample companies. CDS spread is the daily five-year composite credit default swap spread. Historical volatility is for 252 trading days. Implied volatility is the volatility inferred from put options with nonzero open interest. Market capitalization is the product of the stock price and shares outstanding. Leverage ratio is total liabilities divided by the sum of total liabilities and market capitalization.

The CreditGrades Model

To address the nonlinear dependence of the CDS spread on its determinants, we conducted a pricing analysis by using the CreditGrades model, a structural credit risk model in which equity volatility is calculated with information from either the options market or the stock market. Although a full menu of structural models has been developed following the seminal work of Merton (1974), we chose the CreditGrades 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 generate realistic short-term credit spreads. Third, it yields a simple, analytic CDS pricing formula. Although we are aware of the general concern about model misspecification when choosing to work with a particular model, our methodology is applicable to other structural models in a straightforward manner, which we leave for future research.

Under the pricing measure, the CreditGrades model assumes that the company'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 company's debt per share is a constant D, and the (uncertain) default threshold as a percentage of debt per share is

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

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

We defined default 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 into a fixed boundary over the distribution of L. The CreditGrades model, however, provides an approximate solution to the survival probability, $q(t)$, by using a time-shifted Brownian motion, which yields the following result:[2]

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

where

$\Phi(\cdot)$ = the cumulative normal distribution function

$$d = \frac{V_0}{\bar{L}D}e^{\lambda^2}$$

$$A_t = \sqrt{\sigma^2 t + \lambda^2}$$

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

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

Substituting $q(t)$ into Equation 4, 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

$$H(T) = e^{r\xi}[G(T+\xi) - G(\xi)]$$

$$G(T) = d^{z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}} - z\sigma\sqrt{T}\right) + d^{-z+1/2}\Phi\left(-\frac{\ln d}{\sigma\sqrt{T}} + z\sigma\sqrt{T}\right)$$

$$\xi = \lambda^2/\sigma^2$$

$$z = \sqrt{1/4 + 2r/\sigma^2}$$

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

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

where σ_S is the implied volatility from equity options, also produces accurate CDS spreads.

Comparing the CreditGrades model with the I^2 model of Giesecke and Goldberg (2004) in regard to their treatment of the uncertain default barrier, we can see that their default barrier follows a beta distribution, with its mean calibrated to Compustat's short-term debt and its variance treated as a constant parameter. Therefore, as a company adjusts its capital structure over time, the mean default threshold will vary in the I^2 model. In the CreditGrades model, the default barrier is equal to the debt per share (measured in our study by total liabilities per share) multiplied by a normal random variable, with its mean and variance treated as constant parameters. Thus, in both the CreditGrades model and the I^2 model, the mean default barrier changes over time with the capital structure of the company.

Estimation Procedure and Results

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

$$\widehat{CDS}_t = f\left(S_t, D_t, r_t, \sigma_t, T - t; \bar{L}, \lambda, R\right), \quad (7)$$

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

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

Table 2 presents the estimated parameters and the pricing errors. Across the 332 companies, the average parameters are similar for both implied volatility–based and historical volatility–based estimation. In the latter case, the average default threshold $(\bar{L})$ was 0.45, the default threshold uncertainty (λ) was 0.46, and the bond recovery rate (R) was 0.56. In comparison, Finger (2002) assumed that $\bar{L}$ = 0.5 and λ = 0.3 and took R from a proprietary database of J.P. Morgan. These values are reasonably close to the cross-sectional average parameter estimates presented earlier.

Table 2 also presents the cross-sectional average of the average pricing error, the average absolute pricing error, and the root-mean-square pricing error (RMSE) on the basis of both CDS spread levels and percentage deviations from observed levels.[3] Generally, the estimation based on implied volatility yielded smaller fitting errors. For instance, the implied volatility–based RMSE was 105.76 bps, whereas its historical volatility–based counterpart was 131.54 bps. In regard to average pricing errors, the implied volatility–based and historical volatility–based pricing errors were –14.13 bps and –50.31 bps, respectively. Similarly, the implied volatility–based percentage RMSE was 0.60, whereas the historical volatility–based percentage RMSE was 0.72.

To check whether the pricing errors varied among various groups of companies, we partitioned the sample companies into three groups according to their sample CDS spread volatility (the standard deviation of the CDS spread divided by the mean CDS spread). **Table 3** reports the results. We found that the implied volatility

Table 2. Estimated Parameters and Pricing Errors, January 2007–October 2009

	Implied Volatility		Historical Volatility	
	Mean	Standard Error	Mean	Standard Error
Estimated parameters				
$\bar{L}$	0.60	0.03	0.45	0.03
λ	0.47	0.01	0.46	0.01
R	0.58	0.01	0.56	0.01
Pricing errors (bps)				
Average pricing error	–14.13	2.97	–50.31	5.04
Average absolute pricing error	72.23	3.41	96.69	5.45
RMSE	105.76	6.28	131.54	9.23
Percentage pricing errors				
Average pricing error	–0.23	0.02	–0.44	0.02
Average absolute pricing error	0.51	0.01	0.64	0.01
RMSE	0.60	0.01	0.72	0.01

Notes: This table presents cross-sectional averages and standard errors of estimated parameters and pricing errors. For each company, the CreditGrades model was estimated by using either option-implied volatility or 252-day historical volatility as an input. The estimated parameters and pricing errors were then averaged across 332 sample companies. $\bar{L}$ is the expected default threshold, λ is the default threshold uncertainty, and R is the recovery rate. For pricing errors and percentage pricing errors, we report the average pricing error, the average absolute pricing error, and the root-mean-square pricing error (RMSE).

Table 3. Pricing Errors Partitioned by CDS Spread Volatility, January 2007–October 2009

	Group 1 (least volatile)		Group 2		Group 3 (most volatile)	
	Implied Volatility	Historical Volatility	Implied Volatility	Historical Volatility	Implied Volatility	Historical Volatility
Pricing errors (bps)						
Average pricing error	–22.61	–41.96	–13.40	–44.01	–6.46	–64.89
Average absolute pricing error	75.47	89.29	64.99	87.45	76.27	113.25
RMSE	94.40	106.04	89.46	113.06	133.33	175.30
Percentage pricing errors						
Average pricing error	–0.29	–0.40	–0.28	–0.48	–0.13	–0.45
Average absolute pricing error	0.55	0.60	0.55	0.66	0.45	0.65
RMSE	0.62	0.68	0.63	0.74	0.54	0.73

Notes: This table presents cross-sectional averages of pricing errors partitioned by CDS spread volatility (standard deviation of the CDS spread divided by its mean). For each company, the CreditGrades model was estimated by using either option-implied volatility or 252-day historical volatility as an input. The pricing errors were then averaged across sample companies in each subgroup. For pricing errors and percentage pricing errors, we report the average pricing error, the average absolute pricing error, and the RMSE.

yielded significantly smaller pricing errors in the most volatile group of companies. This finding motivated us to investigate the cross-sectional differences in pricing errors.

Cross-Sectional Analysis of Pricing Errors

To examine the balance between historical and implied volatility–based pricing errors, we constructed 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 varied substantially in the cross section, with a median value of 0.83. This observation suggests that although implied volatility yielded smaller pricing errors than historical volatility across our entire sample, a subset of the companies might have significantly smaller pricing errors if implied volatility was used in lieu of historical volatility in calibrating the model. Therefore, we conducted cross-sectional regressions with Ratio_RMSE as the dependent variable and investigated whether certain company-level characteristics are related to this ratio.

When choosing the appropriate company-level characteristics, we were motivated by recent studies that examined the role of options and CDS market information in forecasting stock returns. For example, Acharya and Johnson (2007) suggested 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) showed that call option volume and next-day stock returns are strongly correlated before takeover announcements but are unrelated during normal sample periods. Pan and Poteshman (2006) found a predictive relationship between option volume and future stock returns that

Table 4. Properties of Cross-Sectional Regression Variables, January 2007–October 2009

	Mean	Q1	Median	Q3	Standard Deviation
Ratio_RMSE	0.85	0.63	0.83	1.04	0.30
CDS spread volatility	0.60	0.46	0.60	0.76	0.25
Option volume	0.10	0.05	0.08	0.14	0.07
Option open interest	0.03	0.01	0.02	0.04	0.03
Leverage ratio	0.44	0.31	0.44	0.54	0.16
Total assets ($ billions)	22.28	4.70	9.91	21.92	53.61
Rating	3.97	3.00	4.00	4.62	0.98

Notes: This table presents summary statistics of the cross-sectional regression variables for 332 sample companies. Ratio_RMSE is the implied volatility–based percentage RMSE divided by the 252-day historical volatility–based percentage RMSE. CDS spread volatility is the standard deviation of the CDS spread divided by its mean. 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 each credit rating into a numerical grade, we used the following convention: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, and CCC or below = 7.

becomes stronger with 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 companies. Thus, we included 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 companies with different credit ratings. Among the sample companies, we observed a broad spectrum of credit quality, ranging from AAA (investment-grade) to CCC (speculative-grade), and noted that information asymmetry is expected to be larger for lower-rated companies. Banks and other informed traders/insiders are likely to explore their information advantage in both the CDS and options markets among these lower-rated companies, not higher-rated companies with fewer credit risk problems. Therefore, we included credit rating as another explanatory variable.

Finally, we also included option volume and open interest in our analysis. Although some have argued that informed investors prefer to trade options because of options' inherent leverage, the success of their strategy depends on sufficient market liquidity. To the extent that market illiquidity or trading costs constitute a barrier to entry, we would expect the signal-to-noise ratio of implied volatility to be higher for companies with better options market liquidity. Specifically, we normalized option volume by stock volume and open interest by the total common shares outstanding for each company and each day in the sample period. We normalized option volume and open interest to facilitate comparison across companies. We used option open interest in addition to option volume because the former does not suffer from the double counting of offsetting transactions. Table 4 presents the summary statistics of the regression variables. Note that the majority of sample companies are large investment-grade companies with a median rating of BBB.[4]

Table 5 presents the results of the regression of the pricing error ratio. We found Ratio_RMSE to be smaller for companies with higher CDS spread volatility, higher option trading volume, and lower credit ratings. Moreover, total assets and option open interest were significant in Regression 2 (with a negative sign). To put these coefficients (in Regression 3) into perspective, let us consider the mean value of Ratio_RMSE at 0.85. A one-standard-deviation increase in the CDS spread volatility would lower the ratio to 0.77. A one-standard-deviation increase in the option volume would lower it further, to 0.71. Lowering the credit rating by one standard deviation would reduce Ratio_RMSE further still, to 0.64. For companies

Table 5. Cross-Sectional Regression Analysis of Structural Model Pricing Errors, January 2007–October 2009
(*t*-statistics in parentheses)

	1	2	3
Intercept	1.43***	1.35***	1.46***
	(16.92)	(16.19)	(15.68)
CDS spread volatility	–0.34***	–0.36***	–0.34***
	(–5.60)	(–5.84)	(–5.56)
Option volume	–0.70***	—	–0.86**
	(–3.11)	—	(–2.51)
Option open interest	—	–0.96*	0.47
	—	(–1.93)	(0.62)
Leverage	–0.11	–0.02	–0.13
	(–0.94)	(–0.21)	(–1.08)
Total assets (divided by 100)	–0.05	–0.08*	–0.04
	(–1.04)	(–1.77)	(–0.90)
Rating	–0.06***	–0.06***	–0.07***
	(–3.15)	(–2.73)	(–3.18)
Adjusted R^2	15%	14%	15%

Notes: See notes to Table 4. This table presents coefficients, *t*-statistics, and adjusted R^2s of cross-sectional regressions for 332 sample companies. The dependent variable is Ratio_RMSE, which is the implied volatility–based percentage RMSE divided by the 252-day historical volatility–based percentage RMSE.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

with higher CDS spread volatility, higher option volume, and lower credit ratings, implied volatility appears to be especially useful for explaining CDS spreads, which results in substantially smaller structural model pricing errors vis-à-vis a model calibrated with historical volatility.

Robustness Checks

We conducted several robustness checks.

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 then conducted an out-of-sample pricing analysis in an attempt to capture what investors would experience if they used implied volatility or historical volatility to forecast the CDS spread. Specifically, for each day t in the sample period, we used a rolling window (of the past 252 observations, including day t) to recalibrate the model, following the estimation method outlined earlier.[5] We then used the recalibrated parameters and the day $t + 1$ inputs to compute a CDS spread for day $t + 1$. This procedure allowed us to calculate both implied volatility–based and historical volatility–based out-of-sample pricing errors.

Table 6 presents our findings. Compared with the results in Table 2, the rolling-window estimation generated greater pricing errors, likely because we had to set aside the first 252 daily observations to estimate the CreditGrades model; hence, we computed the out-of-sample pricing errors only for 2008–2009, a much more volatile period than 2007. Nevertheless, a cross-sectional analysis in which we used the ratio of these pricing errors (see **Table 7**) produced 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 greater) for companies with more volatile CDS spreads, larger option volume and open interest, greater leverage, and lower credit ratings.

In light of the well-known difficulty of using structural models to explain changes in the credit spread (Collin-Dufresne, Goldstein, and Martin 2001), we used the CreditGrades model to generate forecasts of credit spread changes, which we defined as the difference between the day $t + 1$ credit spread predicted by the CreditGrades model (following the earlier procedure) and the actual day t credit spread. We then regressed actual credit spread changes on the forecasted ones. **Table 8** shows that when using historical volatility in this forecasting exercise, the resulting forecasts of credit spread changes do not have significant explanatory power for actual credit spread changes. In contrast, when using option-implied volatility, the forecasted credit spread changes have highly significant coefficients in the regression and the average adjusted R^2 is about 4 percent. The size of the implied volatility–based coefficient and the size of the associated R^2 are consistent with the results for explaining credit spread changes with the Chicago Board Options Exchange Market Volatility Index or realized volatility from Collin-Dufresne, Goldstein,

Table 6. Properties of Estimated Parameters and Out-of-Sample Pricing Errors with a 252-Day Rolling Window, January 2007–October 2009

	Implied Volatility		Historical Volatility	
	Mean	Standard Error	Mean	Standard Error
Estimated parameters				
$\overline{L}$	0.72	0.03	0.95	0.02
λ	0.41	0.01	0.40	0.00
R	0.58	0.00	0.54	0.00
Pricing errors (bps)				
Average pricing error	0.25	4.67	70.89	5.11
Average absolute pricing error	93.46	5.11	109.43	6.07
RMSE	136.20	8.67	146.59	9.03
Percentage pricing errors				
Average pricing error	0.02	0.01	0.44	0.03
Average absolute pricing error	0.48	0.01	0.56	0.03
RMSE	0.64	0.02	0.73	0.04

Notes: See notes to Table 2. 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 332 sample companies. For each day, the rolling estimation window is the previous 252 trading days. The one-day-ahead out-of-sample forecast was calculated by using the estimated parameters and the next day's inputs.

Table 7. Cross-Sectional Regression Analysis of Structural Model Out-of-Sample Pricing Errors with a 252-Day Rolling Window, January 2007–October 2009
(t-statistics in parentheses)

	1	2	3
Intercept	1.86***	1.75***	1.88***
	(17.95)	(17.16)	(16.54)
CDS spread volatility	–0.45***	–0.47***	–0.45***
	(–6.00)	(–6.24)	(–5.97)
Option volume	–0.91***	—	–1.04**
	(–3.29)	—	(–2.48)
Option open interest	—	–1.32**	0.40
	—	(–2.18)	(0.44)
Leverage	–0.46***	–0.35**	–0.48***
	(–3.32)	(–2.59)	(–3.31)
Total assets (divided by 100)	–0.01	–0.05	–0.00
	(–0.09)	(–0.83)	(–0.01)
Rating	–0.09***	–0.08***	–0.09***
	(–3.46)	(–2.98)	(–3.42)
Adjusted R^2	23%	22%	23%

Notes: See notes to Table 5. This table presents coefficients, t-statistics, and adjusted R^2s of cross-sectional regressions for 332 sample companies. For each day, the rolling estimation window is the previous 252 trading days. The one-day-ahead out-of-sample forecast was calculated by using the estimated parameters and the next day's inputs. The dependent variable is Ratio_RMSE_Out, which is the out-of-sample implied volatility–based percentage RMSE divided by the out-of-sample 252-day historical volatility–based percentage RMSE.

**Significant at the 5 percent level.
***Significant at the 1 percent level.

Table 8. Time-Series Regression Analysis of Changes in CDS Spreads, January 2007–October 2009
(t-statistics in parentheses)

	Implied Volatility	Historical Volatility
β_0	0.38	0.08
	(–0.03)	(0.05)
β_1	0.02	0.00
	(3.87)	(0.17)
Adjusted R^2	4.12%	0.22%

Notes: This table reports the *average* coefficients and t-statistics of the 332 sample companies for the following regression:

$$CDS_{t+1} - CDS_t = \beta_0 + \beta_1 \left(\widehat{CDS}_{t+1} - CDS_t \right) + \varepsilon_{t+1},$$

where CDS_t is the actual CDS spread at day t and $\widehat{CDS}_{t+1}$ is the one-day-ahead forecast of the CDS spread, calculated by using the parameters from the rolling-window estimation of the previous 252 days and the next day's inputs. The CreditGrades model was estimated with either the option-implied volatility or the 252-day historical volatility.

and Martin (2001) and Zhang, Zhou, and Zhu (2009). Overall, implied volatility–based calibration produces not only smaller in-sample and out-of-sample fitting errors but also superior forecasts for daily credit spread changes.

Historical Volatilities with Alternative Horizons. Having compared the information content of implied volatility with that of the 252-day historical volatility in predicting CDS spreads, we next looked at historical volatilities with alternative estimation horizons. We especially wanted to consider both the ability of long-dated estimators to produce stable asset volatility measures and the advantage of short-dated estimators in timely adjusting to new market information. Therefore, we repeated our previous pricing analysis with different historical volatility estimators (ranging from 22 days to 1,000 days). The results are presented in **Table 9**. Regardless of whether the pricing error is measured in levels or percentages, it appears to decline with the estimation horizon of the historical volatility estimator. The RMSE ranged from 164 bps for the 22-day historical volatility to 96 bps for the 1,000-day historical volatility. In comparison, implied volatility produced the second-lowest pricing errors among all estimators used. The slight advantage of the 1,000-day historical volatility over implied volatility can probably be attributed to its ability to fit smooth and low levels of the CDS spread.[6]

When we conducted the cross-sectional pricing error ratio analysis in **Table 10**, we found that the results closely resemble those in Table 5—that is, the

Table 9. Estimated Parameters and Pricing Errors for Historical Volatilities with Alternative Horizons, January 2007–October 2009

	Historical Volatility					Implied Volatility
	22 Days	63 Days	126 Days	252 Days	1,000 Days	
Estimated parameters						
$\overline{L}$	0.35	0.47	0.47	0.45	0.95	0.60
λ	0.43	0.44	0.46	0.46	0.45	0.47
R	0.49	0.53	0.55	0.56	0.56	0.58
Pricing errors (bps)						
Average pricing error	–44.71	–22.40	–28.31	–50.31	–35.16	–14.13
Average absolute pricing error	114.04	99.25	94.31	96.69	69.14	72.23
RMSE	163.57	142.69	129.41	131.54	96.15	105.76
Percentage pricing errors						
Average pricing error	–0.56	–0.40	–0.41	–0.44	–0.18	–0.23
Average absolute pricing error	0.79	0.69	0.65	0.64	0.43	0.51
RMSE	0.87	0.77	0.72	0.72	0.49	0.60

Notes: See notes to Table 2. This table reports the cross-sectional averages of estimated parameters and pricing errors.

Table 10. Cross-Sectional Regression Analysis of Structural Model Pricing Errors for Historical Volatilities with Alternative Horizons, January 2007–October 2009
(*t*-statistics in parentheses)

	22 Days	63 Days	126 Days	252 Days	1,000 Days
Intercept	1.06***	1.05***	1.20***	1.46***	2.20***
	(17.31)	(17.63)	(16.17)	(15.68)	(13.96)
CDS spread volatility	–0.21***	–0.14***	–0.18***	–0.34***	–0.45***
	(–5.30)	(–3.56)	(–3.58)	(–5.56)	(–4.38)
Option volume	–0.59***	–0.52**	–0.51*	–0.86**	–1.51***
	(–2.59)	(–2.35)	(–1.85)	(–2.51)	(–2.60)
Option open interest	0.80	0.30	–0.05	0.47	1.63
	(1.61)	(0.62)	(–0.09)	(0.62)	(1.28)
Leverage	0.05	0.07	–0.03	–0.13	–0.08
	(0.70)	(0.88)	(–0.36)	(–1.08)	(–0.38)
Total assets (divided by 100)	–0.01	–0.01	–0.02	–0.04	–0.18**
	(–0.43)	(–0.22)	(–0.55)	(–0.90)	(–2.21)
Rating	–0.06***	–0.04***	–0.05***	–0.07***	–0.12***
	(–3.98)	(–2.86)	(–2.67)	(–3.18)	(–3.40)
Adjusted R^2	11%	6%	8%	15%	12%

Notes: See notes to Table 5. This table presents coefficients, *t*-statistics, and adjusted R^2s of cross-sectional regressions with historical volatilities of alternative horizons for 332 sample companies. The dependent variable is Ratio_RMSE, which is the implied volatility–based percentage RMSE divided by the historical volatility–based percentage RMSE of alternative horizons.

*Significant at the 10 percent level.
**Significant at the 5 percent level.
***Significant at the 1 percent level.

Ratio_RMSE variable is lower for companies with higher CDS spread volatility, higher option volume, and lower credit ratings. Therefore, even though the pricing performance varies among the various historical volatility inputs used in the calibration, implied volatility continues to be more informative in the same subset of companies identified by our earlier analysis. Overall, these additional analyses confirm that the information advantage of implied volatility is robust to historical volatility estimators of various horizons.

Conclusion

Can we use information from the options market to do a better job of pricing credit derivatives? How does the performance of CDS pricing under option-implied volatility vary with the degree of information asymmetry and market frictions? Using a large sample of companies with both CDS and options data available, we found that option-implied volatility dominates historical volatility in fitting CDS spreads to the CreditGrades model. Moreover, we found that the need to use option-implied volatility is more imperative with a larger presence of informed/insider trading and when the options market is more liquid. Our robustness checks confirmed that our findings are insensitive to a rolling-window estimation approach and to historical volatilities estimated with various horizons.

This article qualifies for 1 CE credit.

Notes

1. In a previous version of this article, we used CDS and options market data from an earlier sample period (2001–2004). Compared with 2007–2009, the overall levels of market volatility and CDS spreads were lower and the CreditGrades model pricing errors were smaller. The main findings of our analysis, however, remain qualitatively unchanged—namely, implied volatility dominates historical volatility in CDS pricing performance, and the comparative advantage is more striking among companies with higher options-trading volume, more volatile CDS spreads, and lower credit ratings.
2. The approximation assumes that W_t starts at a time earlier than $t = 0$. In essence, the uncertainty in the default threshold is shifted to the starting value of the Brownian motion.
3. Note that we minimized the sum of squared relative pricing errors to obtain the estimated model parameters. We obtained qualitatively similar results by minimizing the pricing errors measured in CDS spread levels.
4. To convert each credit rating into a numerical grade, we used the following convention: AAA = 1, AA = 2, A = 3, BBB = 4, BB = 5, B = 6, and CCC = 7.
5. Using 22-day and 126-day rolling windows in the same test, we found that our main results were unchanged. Although not reported here, these results are available upon request.
6. To see the logic behind this argument, assume that the observed spread is 200 bps. A fitted spread of 500 bps yields a relative pricing error of 150 percent. When the observed spread is 500 bps, a fitted spread of 200 bps 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 low spreads.

References

Acharya, V., and T. Johnson. 2007. "Insider Trading in Credit Derivatives." *Journal of Financial Economics*, vol. 84, no. 1 (April):110–141.

Back, K. 1993. "Asymmetric Information and Options." *Review of Financial Studies*, vol. 6, no. 3 (July):435–472.

Black, F. 1975. "Fact and Fantasy in the Use of Options." *Financial Analysts Journal*, vol. 31, no. 4 (July/August):36–41.

Black, F., and J.C. Cox. 1976. "Valuing Corporate Securities: Some Effects of Bond Indenture Provisions." *Journal of Finance*, vol. 31, no. 2 (May):351–367.

Campbell, J.Y., and G.B. Taksler. 2003. "Equity Volatility and Corporate Bond Yields." *Journal of Finance*, vol. 58, no. 6 (December):2321–2350.

Cao, C., Z. Chen, and J. Griffin. 2005. "Informational Content of Option Volume Prior to Takeovers." *Journal of Business*, vol. 78, no. 3 (May):1073–1109.

Cao, C., F. Yu, and Z. Zhong. 2010. "The Information Content of Option-Implied Volatility for Credit Default Swap Valuation." *Journal of Financial Markets*, vol. 13, no. 3 (August):321–343.

Collin-Dufresne, P., R. Goldstein, and S. Martin. 2001. "The Determinants of Credit Spread Changes." *Journal of Finance*, vol. 56, no. 6 (December):2177–2207.

Cremers, M., J. Driessen, P. Maenhout, and D. Weinbaum. 2008. "Individual Stock Option Prices and Credit Spreads." *Journal of Banking & Finance*, vol. 32, no. 12 (December):2706–2715.

Currie, A., and J. Morris. 2002. "And Now for Capital Structure Arbitrage." *Euromoney* (December):38–43.

Easley, D., M. O'Hara, and P. Srinivas. 1998. "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade." *Journal of Finance*, vol. 53, no. 2 (April):431–465.

Ericsson, J., K. Jacobs, and R. Oviedo. 2009. "The Determinants of Credit Default Swap Premia." *Journal of Financial and Quantitative Analysis*, vol. 44, no. 1 (February):109–132.

Finger, C.C., ed. 2002. "CreditGrades Technical Document." RiskMetrics Group (May): www.creditrisk.ru/publications/files_attached/cgtechdoc.pdf.

Giesecke, K., and L. Goldberg. 2004. "Forecasting Default in the Face of Uncertainty." *Journal of Derivatives*, vol. 12, no. 1 (Fall):11–25.

Luo, Y. 2008. "Risk and Return of Capital Structure Arbitrage with Credit Default Swaps." PhD dissertation, University of California, Irvine.

Merton, R.C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*, vol. 29, no. 2 (May):449–470.

Pan, J., and A. Poteshman. 2006. "The Information in Option Volume for Future Stock Prices." *Review of Financial Studies*, vol. 19, no. 3 (Fall):871–908.

Stamicar, R., and C.C. Finger. 2006. "Incorporating Equity Derivatives into the CreditGrades Model." *Journal of Credit Risk*, vol. 2, no. 1 (Spring):1–20.

Yu, F. 2006. "How Profitable Is Capital Structure Arbitrage?" *Financial Analysts Journal*, vol. 62, no. 5 (September/October):47–62.

Zhang, B.Y., H. Zhou, and H. Zhu. 2009. "Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms." *Review of Financial Studies*, vol. 22, no. 12 (December):5099–5131.

