How Important Is Option-Implied Volatility for Pricing Credit Default Swaps?

Charles Cao   Fan Yu   Zhaodong Zhong[1]

First Draft: November 12, 2005

Current Version: October 4, 2006

[1]Cao and Zhong are from the Smeal College of Business at the Pennsylvania State University, Email: charles@loki.smeal.psu.edu, and zxz126@psu.edu. Yu is from the Paul Merage School of Business at the University of California, Irvine, Email: fanyu@uci.edu. We thank Mikhail Chernov, Peter Christofferson, Robert Jarrow, Philippe Jorion, Mark Kamstra, Bill Kracaw, Paul Kupiec, Tom McNerney, Til Schuermann, Stuart Turnbull, Hao Zhou, and seminar/conference participants at Pennsylvania State University, the McGill/IFM^2 Risk Management Conference, and the 16th Annual Derivatives Securities and Risk Management Conference for helpful comments. We also acknowledge the financial support of the FDIC's Center for Financial Research.

How Important Is Option-Implied Volatility for Pricing Credit Default Swaps?

Abstract

This paper empirically examines the role of option-implied volatility in determining the credit default swap (CDS) spread. Using firm-level time-series regressions, we find that implied volatility dominates historical volatility in explaining CDS spreads. More importantly, the advantage of implied volatility is concentrated among firms with lower credit ratings, higher option volume and open interest, and firms that have experienced important credit events such as a significant increase in the level of CDS spreads. To accommodate the inherently nonlinear relation between CDS spread and volatility, we estimate a structural credit risk model called "CreditGrades." Assessing the performance of the model with either implied or historical volatility as input, we reach broadly similar conclusions. Further analysis reveals that for individual stocks, implied volatility generally dominates historical volatility in predicting future volatility. However, the ability of implied volatility to explain CDS spreads stems from a combination of better prediction of future volatility and the volatility risk premium embedded in option prices.

1 Introduction

Credit default swaps (CDS) are a class of credit derivatives that provide a payoff equal to the loss-given-default on bonds or loans of a reference entity, triggered by credit events such as default, bankruptcy, failure to pay, or restructuring. The buyer pays a premium as a percentage of the notional value of the bonds or loans each quarter, denoted as an annualized spread in basis points (bp), and receives the payoff from the seller should a credit event occur prior to the expiration of the contract. Fueled by participation from banks, insurance companies, and hedge funds to take on or shed credit risk exposures, the CDS market has been growing exponentially during the past decade, reaching $26 trillion in notional amount outstanding by the first half of 2006.[1] This level has already surpassed the market size for equity and commodity derivatives.

This dramatic development obviates the need for a better understanding of the pricing of credit risk. In response, a recent strand of literature has recognized the important role of firm-level volatilities in the determination of bond and CDS spreads.[2] Following this literature, we conduct a comprehensive analysis of the relation between equity volatility and CDS spreads. What sets this study apart from the extant literature is our focus on the economic intuition behind the information content of option-implied volatility for credit default swap valuation.

Consider the choices facing an informed trader who possesses private information regarding the credit risk of an obligor. She could trade on this information in a range of different venues, such as stock, option, bond, and CDS markets. What security she chooses to trade, however, is a function of how sensitive the security prices are with respect to the private information, the relative liquidity of the markets, and the degree of information asymmetry in the markets. This is essentially the conclusion reached in the theoretical model of Easley, O'Hara, and Srinivas (1998). In their "pooling equilibrium" in which the

[1] For details, see the International Swaps and Derivatives Association Market Survey.

[2] See Campbell and Taksler (2003), Cremers, Drissen, Maenhout, and Weinbaum (2004), Ericsson, Jacobs, and Oviedo-Helfenberger (2004), Avramov, Jostova, and Philipov (2004), and Zhang, Zhou, and Zhu (2005), among others.

informed trader trades through both the CDS and the option market, there should be a link between the CDS spread and the option-implied volatility (IV).

We conjecture that the CDS-IV relation is stronger among firms with higher-than-average option volume, option open interest, and CDS spread volatility.[3] The first two variables can be considered as proxies of option market liquidity, and the last variable a proxy of the degree of information asymmetry in the markets. To the extent that trading cost or market illiquidity constitutes a "barrier to entry," the degree of information asymmetry needs to be sufficiently high for informed traders to trade in a given market. This has motivated Cao, Chen, and Griffin (2005) to study the information content of option volume for future stock returns around takeover announcements, when the degree of asymmetric information is likely to be high. Without resorting to event studies, the CDS spread volatility measure allows us to zero in on many recent accounting scandals, which often resulted in skyrocketing CDS spreads and heightened CDS spread volatility for the implicated parties.

Specifically, we conduct firm-level time-series regressions of the CDS spread on implied volatility and historical volatility, controlling for other determinants of credit spreads used in the literature.[4] Our sample comes from the intersection of a CDS dataset provided by the Markit Group, with daily spreads of five-year CDS on North American obligors, and OptionMetrics, which contains daily prices on all exchange-listed U.S. equity options. These extensive coverages allow us to generate a sample of daily CDS spreads and implied volatilities, covering 220 firms from 2001 to 2004. We divide the firms into sub-groups based on their CDS spread volatility, option trading volume and open interest, and credit rating. We find that both the size and the statistical significance of the implied volatility coefficient increase monotonically with these category variables. Meanwhile, the 252-day historical volatility is at best marginally significant in the presence of implied volatility, and often loses its significance precisely when implied volatility is the most informative for CDS

[3]The option volume and open interest are scaled by their stock market counterparts, and the firm-level CDS spread volatility is equal to the standard deviation of the CDS spread scaled by its mean over the entire sample period.

[4]Most of the existing studies use a panel regression framework to estimate the effect of equity volatility on credit spreads. As such, they do not analyze the informativeness of implied volatility in a cross-sectional context as we do here.

spreads. Overall, our regression results suggest that implied volatility dominates historical volatility in explaining the time-variation of CDS spreads. More importantly, it works best for speculative-grade obligors with highly volatile CDS spreads and actively-traded equity options.

[Insert Figure 1 here.]

To effectively address the inherently nonlinear relation between CDS spreads and equity volatility, we estimate a structural credit risk model called "CreditGrades" for each firm in our sample using either implied volatility or the 252-day historical volatility as input.[5] Interestingly, while the CreditGrades Technical Document (2002) recommends the 1,000-day historical volatility as an input to the model, it uses a case study of Worldcom to suggest that "The long-term historical volatility estimator used in CreditGrades is robust in reasonably stable periods. However, when a firm's stock or credit moves suddenly, the historical volatility can lag true market levels. In these cases, it is constructive to examine implied volatility levels." The rationale for relying on implied volatility as an input to the model is evident from Figure 1, where we fit the CreditGrades model to AT&T CDS spreads using either the 252-day historical volatility or the option-implied volatility. This figure shows that the use of implied volatility yields a much better fit to the market spread around the telecommunication industry meltdown in mid-2002, when the AT&T spread shot up from 200bp to 700bp.

More generally, we minimize firm-level sum of squared pricing errors over the three parameters of the CreditGrades model: the mean default threshold, the default threshold uncertainty, and the bond recovery rate. Across the entire sample, we find that implied volatility provides a better fit to market spreads than the 252-day historical volatility, with a firm-level pricing error that is about 25 percent less on average. In addition, we

[5]In 2002, RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank jointly developed CreditGrades, an industry benchmark model for evaluating CDS spreads, which is based on the structural model of Black and Cox (1976). Since then it has become widely adopted among practitioners as a tool for identifying relative value trading opportunities in the CDS and equity markets. For a description of the so-called "capital structure arbitrage" using the CreditGrades model, see Currie and Morris (2002). For an analysis of its risk and return, see Duarte, Longstaff, and Yu (2005) and Yu (2006).

compute the ratio of the implied volatility-based pricing error to the historical volatility-based pricing error for each firm. Using cross-sectional regressions, we find that this pricing error ratio is smaller for firms with lower credit ratings, larger total assets, higher option open interest, and more volatile CDS spreads. These findings are in apparent agreement with our regression-based results, and lend support to the practice of calibrating structural models to implied volatility in a turbulent market.

To further examine the robustness of our results, we apply the regression and pricing analyses to 22-, 63-, 126-, and 1,000-day historical volatility estimators. Consistent with the recommendation of the CreditGrades Technical Document (2002), the in-sample pricing error associated with the 1,000-day historical volatility is the lowest among all five historical volatility estimators considered. Compared to even this best case, the in-sample pricing error with implied volatility is lower still by another 18 percent on average. In our regression analysis, although the 63-day and 126-day historical volatility coefficients are statistically significant, they are still less than half of the size of the implied volatility coefficients. These observations suggest that the information advantage of implied volatility remains robust to historical volatility estimated at different horizons.

Having investigated the cross-sectional behavior of the CDS-IV relation, an important question nonetheless remains. Namely, is implied volatility able to explain CDS spreads because of its ability to predict future volatility, or the volatility risk premium embedded in option prices? Previous studies produce mixed evidence on the first part of the question, showing that implied volatility is more informative and efficient in markets in which trading cost is small and measurement problems are less of an issue. They also tend to focus on index, currency, and interest rate option markets.[6] Regarding the second part of the question, the difference between implied volatility and expected future volatility under the objective measure is commonly attributed to a volatility risk premium.[7] Presumably, this risk premium component can help explain CDS spreads in a way that even the best volatility

[6] See Amin and Ng (1997), Canina and Figlewski (1993), Christensen and Prabhala (1998), Day and Lewis (1992), Jorion (1995), and Lamoureux and Lastrapes (1993), among others.

[7] See Chernov (2002), Bates (2003), Bakshi and Kapadia (2003), and Bollerslev, Gibson, and Zhou (2006), among others.

estimator cannot.

To fully address these questions, we first regress future realized volatility (FV) on implied and historical volatility. Generally, we find implied volatility to be an informative forecast that tends to dominate historical volatility. Second, we regress CDS spreads on FV and the difference between IV and FV, where the latter variable takes on the interpretation of a volatility risk premium. We find the volatility risk premium to be a significant determinant of CDS spreads even in the presence of FV. Taken together, these results suggest that the ability of implied volatility to explain CDS spreads stems from a combination of better prediction of future volatility and the volatility risk premium embedded in option prices.

The rest of this paper is organized as follows. In Section 2, we explain the major data sources and variables used in our study. In Section 3, we conduct a regression-based analysis of the relation between CDS spreads and implied and historical volatility. In Section 4, we present a pricing analysis of the relation between CDS spreads and the two volatility measures. This section begins with a brief introduction to the CreditGrades model used in the analysis. In Section 5, we present additional results on the use of historical volatility estimators of alternative horizons. In Section 6, we demonstrate the importance of the volatility risk premium in accounting for the CDS-IV relation. We conclude with Section 7.

2 Data

The variables used in our study are obtained from several major data sources. These sources and the associated variables are explained below.

2.1 Credit Default Swaps

First, we take five-year CDS spreads from a comprehensive dataset from the Markit Group.[8] This dataset provides daily CDS spreads on more than 1,000 North American obligors from 2001 to 2004. The daily spreads are calculated from quotes contributed by more than 30 banks, and undergo a statistical procedure where outliers and stale quotes are removed. In addition, three or more contributors are needed before a daily composite spread is computed. This level of coverage is probably the most complete among all CDS datasets available to academic researchers, who increasingly turn to the CDS market for measures of credit risk.

2.2 Equity Options

Second, we obtain options data from OptionMetrics, which provides daily closing prices, open interest, and trading volume on exchange-listed equity options in the U.S. from 1996 to 2004. In addition, this dataset contains a set of implied volatilities for standardized strike prices and maturities, which are generated using interpolation. While it may appear convenient to use the standardized implied volatilities provided by OptionMetrics, we find that they can be quite sensitive to the discrete maturity and moneyness effects. For example, the OptionMetrics 30-day at-the-money put-implied volatility is interpolated from just four put options with strike prices straddling the forward stock price and maturities straddling 30 days. As the included options approach expiration and the stock price changes, one or more of the four options will be replaced by other options, often causing a spurious change in the estimated implied volatility.

Ideally, we would like to extract a daily implied volatility from deep out-of-the-money put options. The value of such options is most sensitive to the left tail of the risk-neutral equity return distribution, as is the CDS spread. However, few firms in our sample have actively traded deep out-of-the-money put options. Therefore, we use the binomial model for American options with discrete dividend adjustments to estimate the level of implied

[8] Although contracts with other maturities are also trades, five-year CDS contracts have become the most common in recent years. For example, Hull, Predescu, and White (2004) estimate that more than 85 percent of the quotes in 2001 and 2002 are for five-year contracts.

volatility that would minimize the sum of squared pricing errors across all put options with nonzero open interest each day. The choice of nonzero open interest emphasizes the information content of options that are currently in use by market participants. The choice of all put options with a wide range of strike prices and maturities, not just the four used by OptionMetrics, reduces the spurious noise in the implied volatility measure introduced by the periodic switching from one contract to another.

Besides the daily implied volatility measure, we also compute an implied volatility skew as the difference between the implied volatility of a put option with a strike-to-spot ratio closest to 0.92 and the at-the-money implied volatility, further divided by the difference in the strike-to-spot ratio. Both put options are expiring in the month immediately after the current month. The implied volatility skew is closely related to the skewness of the risk-neutral equity return distribution. We expect it to be positively related to the CDS spread.[9]

2.3 Other Firm-level and Market-level Variables

Third, we obtain equity prices, common shares outstanding, and daily stock returns from CRSP, and the book value of total liabilities from Computstat. We calculate historical volatility measures with different estimation horizons, ranging from 22, 63, 126, 252, to 1,000 trading days, while our primary analysis is based on the 252-day historical volatility and the option-implied volatility. We also define the leverage ratio as total liabilities divided by the sum of total liabilities and market capitalization. Leverage ratio is one of the key firm-level measures of credit risk according to structural models.

Lastly, we include a list of market variables that can potentially explain a significant part of the time-variation of CDS spreads. These variables are often used in the extant literature to explain bond spreads.[10]

- *Market-level returns and volatilities.* We use the S&P 100 implied volatility and im-

[9] Cremers, Driessen, Maenhout, and Weinbaum (2004) examine the relationship between corporate bond yield spreads and implied volatility skews.

[10] The rationale for including these market-level variables in a time-series regression analysis of credit spreads can be found in Collin-Dufresne, Goldstein, and Martin (2001).

plied volatility skew, and the 252-day average S&P 500 return and historical volatility, obtained from CRSP.

- *Default-free term structure level and slope.* For the term structure level, we use the five-year Treasury yield. For the slope, we calculate the difference between the ten-year and the two-year Treasury yields. Both variables are obtained from Datastream.
- *Market-level credit risk.* We use the Baa yield from Moody's.
- *Bond market liquidity.* We take the ten-year swap yield minus the ten-year Treasury yield, both obtained from Datastream.

2.4 Summary Statistics

We combine all variables documented above to arrive at our final sample for the regression analysis. We eliminate obligors in the financial, utility, and government sectors because of the difficulty in interpreting their capital structure variables. We then require that the obligors have more than 377 observations of the CDS spread, the implied volatility, the 252-day historical volatility, and the leverage ratio. These requirements ensure that each obligor have at least one and a half years of daily data available for the firm-level time-series regression analysis. This leaves us with a final sample of 220 firms from January 2001 to June 2004.

[Insert Table 1 here.]

Table 1 presents the cross-sectional summary statistics of the time-series mean of the variables. The average firm in our sample is quite large, with a market capitalization in excess of $20 billion.[11] The average firm has also done remarkably well during the sample period, with an annualized 252-day moving average stock return of 20.99 percent. In contrast, the annualized 252-day moving average return on the S&P 500 index is only -2.30 percent in the same period. This difference is most likely attributed to a survivorship bias because of the requirement that sample firms must have more than one and a half years

[11]This is in fact close to the average size of S&P 500 companies, which equals $22.5 billion in 2005.

of CDS spread coverage. We also observe that the mean CDS spread is 152bp, although the cross-sectional standard deviation is 216bp, indicating that there are firms with very high levels of CDS spreads in our sample. Indeed, the mean CDS spread of 152bp is much higher than the median CDS spread of 83bp.

For the volatility measures, the average firm-level implied volatility is 38.80 percent, slightly less than the average firm-level historical volatility of 40.43 percent. In contrast, the mean market-level implied volatility is 23.22 percent, slightly higher than the mean market-level historical volatility of 21.48 percent. The mean market implied volatility skew of 1.13 is more than twice as large as the mean firm-level implied volatility skew of 0.55.

[Insert Table 2 here.]

Table 2 reports the distribution of the number of options in various maturity and moneyness categories. Moneyness is defined as the ratio of spot price divided by strike price for calls and strike price divided by spot price for puts. Across all options covered by OptionMetrics, the distribution across moneyness and maturity appears to be fairly uniform. However, only near-the-money options (those with moneyness between 0.8 and 1.2) are heavily traded. While this suggests that we should focus on near-the-money options, options with positive trading volume seem to be a relative minority of the total. On the other hand, the distribution of put options with open interest is similar to the distribution of all options, and they constitute about 40 percent of the total number of options. This is the subset of options from which we compute our daily implied volatility measure.

3 Regression Analysis

In this section we present a regression analysis of the information content of implied volatility for CDS spreads. Following the discussion in Section 2, we use the implied volatility extracted from all put options with nonzero open interest.

3.1 Benchmark Regressions

We conduct time-series regressions for each of the 220 firms, in which the dependent variable is the CDS spread. In Table 3, we start with univariate regressions, pitting the CDS spread against either the 252-day historical volatility (HV) or the implied volatility (IV). We then take the residuals from the first step and regress them on the other volatility measure. Specifically, for Panel A, we sequentially estimate the following regression equations:

$$CDS_t = \alpha_0 + \alpha_1 HV_t + \varepsilon_t, \tag{1}$$

$$\varepsilon_t = \beta_0 + \beta_1 IV_t + \eta_t. \tag{2}$$

In Panel B, we reverse the order of IV and HV in the above equations and repeat the estimation. These regressions are designed to delineate the incremental contribution of historical and implied volatilities toward explaining the time-variation of CDS spreads. In Table 3, we report the cross-sectional averages of coefficient estimates and their t-statistics.

[Insert Table 3 here.]

As Table 3 shows, we find a strong relation between the CDS spread and the two volatility measures that is both statistically and economically significant. A one percent increase in the historical (implied) volatility raises the CDS spread by about 4.14 (5.64) basis points. The volatility coefficients are highly significant, with average regression t-statistics of 12.46 (15.88). Table 3 also presents the percentage of cases out of the 220 individual firm regressions in which the t-statistics are greater than 1.96. For the first-stage regression with historical (implied) volatility, 92 (99) percent have t-statistics greater than 1.96. Another piece of evidence indicating the strong link between historical (implied) volatility and CDS spreads is that the volatility measure alone accounts for 36 (56) percent of the time-series variation of CDS spreads.

While both volatility measures are obviously important, there is some evidence that the implied volatility measure enjoys an edge over historical volatility in explaining CDS spread changes. This is evident from the higher average R^2 (56 vs. 36 percent) in the univariate regressions with implied volatilities, and the fact that implied volatility explains a larger portion of the residuals (23 vs. 9 percent) from the first-stage regressions. It is also reflected in the larger percentage of cases with t-statistics greater than 1.96 when implied volatility is used in the first-stage regressions (99 vs. 92 percent) or in the second-stage regressions (91 vs. 45 percent).

In Table 4, we expand the set of regressors to include additional variables as described in Section 2. The regression equation is the following:

$$\begin{aligned} CDS_t &= \alpha + \beta_1 HV_t + \beta_2 IV_t + \text{additional firm-specific variables} + \\ &\quad \text{market volatility variables} + \text{macro variables}. \end{aligned} \tag{3}$$

We find that the effect of these additional variables on the CDS spread, if any, is consistent with theoretical predictions and the extant empirical evidence. For example, the average coefficient on the firm implied volatility skew is positive, although generally not statistically significant. This accords with the implied volatility skew being a proxy of the risk-neutral skewness of the stock return distribution—the larger the skew, the higher the probability of default and the CDS spread. For the other firm-specific variables, the average coefficient on the firm leverage ratio is positive but not significant, and the firm stock return appears insignificant.

[Insert Table 4 here.]

Among the market variables, we observe negative coefficients for the Treasury term structure level and slope. This is consistent with the evidence from corporate bond yield spreads.[12] The coefficient for the Baa yield is positive and significant, which can be attributed to the close relationship between bond and CDS markets.[13] In addition, we find that none of the market volatility variables are significant. This suggests that the information content of market-level volatilities is subsumed by firm-level volatilities.

With this list of additional variables included in the regressions, the average R^2 of the time-series regressions has increased from 63 percent in Regression One to 85 percent in

[12] See Duffee (1998).

[13] See Longstaff, Mithal, and Neis (2005) and Blanco, Brennan, and Marsh (2005).

Regression Four. We notice that in the most exhaustive Regression Four, the firm-level implied volatility still comes up significant, with an average t-statistics of 4.41. In contrast, the firm historical volatility becomes insignificant with an average t-statistics of only 1.26. The cross-sectional distribution of t-statistics appears to be tighter for implied volatility than for historical volatility—the former has 73 percent of cases out of 220 with t-statistics greater than 1.96, while the latter has only 44 percent such cases. We also conduct a one-sided test of whether the implied volatility coefficient (β_2) is greater than the historical volatility coefficient (β_1). At the ten percent significance level, we find that in 46 percent of the cases we would reject $\beta_2 = \beta_1$ in favor of $\beta_2 > \beta_1$. On the other hand, we would reject $\beta_1 = \beta_2$ in favor of $\beta_1 > \beta_2$ in only 23 percent of the cases.[14]

Overall, both the 252-day historical volatility and the option-implied volatility can individually explain a significant part of the time-variation in the CDS spread. However, when both are included in the same regression, it is generally the case that the implied volatility dominates the 252-day historical volatility in its informativeness for CDS spreads.

3.2 By CDS Spread Volatility

To further understand the advantage of implied volatility over historical volatility in explaining CDS spreads, we divide our sample firms according to several firm-level characteristics and summarize the regression results for each sub-group.

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, Cao, Chen, and Griffin (2005) show that call option trading 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. Acharya and Johnson (2005) suggest

[14] We also test for the significance of the average coefficient using the cross-sectional distribution of the estimated firm-level coefficients. Our results show that the average β_2 is much larger and more significant than the average β_1.

that the incremental information revelation in the CDS market relative to the stock market is driven by banks trading on their private information. To the extent that heightened volatility in the CDS market is an indication of informed trading, option-implied volatility can be especially helpful in explaining CDS spreads at such times. We therefore sort the firms according to their CDS spread volatility. For each firm, this is defined as the sample standard deviation of the CDS spread normalized by its sample mean.

[Insert Table 5 here.]

Table 5 presents evidence supporting this conjecture. For the least volatile group of firms (Group 1), the average coefficient for implied volatility is 0.81 and the average t-statistics is 3.17. However, the average coefficient increases to 1.77 for Group 2 and 6.65 for the most volatile group. The average t-statistics also increases monotonically, to 3.85 for Group 2 and 6.23 for Group 3. The percentage of firms with implied volatility coefficient t-statistics greater than 1.96 is 64 percent for Group 1, 74 percent for Group 2, and 79 percent for Group 3. In contrast, we do not find the coefficient of historical volatility to follow this pattern. Specifically, the average historical volatility coefficients are small and insignificant among the least and the most volatile groups of firms. For the least volatile group, we would reject $\beta_2 = \beta_1$ in favor of $\beta_2 > \beta_1$ in 42 percent of the cases and reject $\beta_1 = \beta_2$ in favor of $\beta_1 > \beta_2$ in 25 percent of the cases. For the most volatile group, these numbers are 59 and 15 percent, respectively. These results confirm a more important role for implied volatility as the CDS market becomes more volatile. Note that even among the least volatile group, the implied volatility appears to be more informative than the historical volatility.

As the volatility of CDS spreads increases, Table 5 shows that they become more sensitive to leverage ratio and a number of market risk variables such as the five-year Treasury yield, the swap spread, and the Baa yield. Because firms with more volatile CDS spreads are also more likely to have higher average CDS spreads, this can be attributed to a nonlinear relation between CDS spreads and the explanatory variables.

3.3 By Option Volume and Open Interest

It is well known that some individual equity options are thinly traded and suffer from liquidity problems. One is then led to expect that the information content of implied volatility would be concealed to some extent by the presence of market microstructure noise in option prices.[15] Therefore, we partition the sample firms according to variables that would proxy for options market liquidity. Specifically, we use the ratio of option volume standardized by its respective stock volume for each firm. We adopt this metric because it is the ease in trading options relative to the underlying stock that is likely to affect the information content of implied volatility. This metric also facilitates our subsequent cross-sectional analysis because the standardized option volume is comparable across firms.

[Insert Table 6 here.]

Indeed, Table 6 shows that implied volatility becomes a more significant regressor as the option-stock volume ratio increases. For Group 1, which comprises of firms with the lowest option-stock volume ratio, the coefficient of implied volatility is 2.33, already more than twice as large as the coefficient on historical volatility. However, it increases further with the option-stock volume ratio, and its statistical significance increases as well. For Group 3, the implied volatility coefficient is 4.29, more than five times the size of the corresponding historical volatility coefficient. The relationship between the implied volatility coefficient and the option-stock volume ratio groups appears to be monotonic, which is also reflected in the percentage of β_2 with t-statistics greater than 1.96 (66, 73, and 79 percent, respectively). In contrast, the size of the historical volatility coefficient is the smallest among the group with the largest option-stock volume ratio, where the average t-statistic is merely 1.17 for historical volatility, but 5.99 for implied volatility. Moreover, our one-sided coefficient tests seem to return more cases with $\beta_2 > \beta_1$ and fewer cases with $\beta_1 > \beta_2$ as the option-stock volume ratio increases.

[15]For example, Donaldson and Kamstra (2005) find that implied volatility is more informative than ARCH for volatility forecasting when the stock market volume is higher than normal.

Interestingly, the firm-level implied volatility is the only independent variable whose coefficient becomes larger and more significant with the option-stock volume ratio. The coefficients of other independent variables, such as the leverage ratio and the Baa yield, are either insignificant or do not change significantly across the option-stock volume ratio groups. Taken together with the behavior of the implied volatility coefficient, we conclude that the information content of implied volatility for CDS spreads depends strongly on the liquidity of the options market.

In addition to the option volume metric, we investigate an alternative measure of the quality of options market information, the open interest. In some sense, the open interest is a better measure of the size of the options market because it does not suffer from the double counting of offsetting transactions. For each firm, we construct a normalized measure by dividing the option open interest by the total common shares outstanding. Our results, which are not included here, largely confirm the findings with the option-stock volume ratio. Namely, the coefficient on historical volatility is insignificant, while the coefficient on implied volatility is consistently significant and becomes the largest in the group with the highest option open interest.

3.4 By Credit Rating

Among our sample firms, we observe a broad spectrum of different credit quality, ranging from AAA (investment-grade) to CCC (speculative-grade).[16] An important question is whether the information content of implied volatility for CDS spreads would vary across firms with different credit ratings. Because the credit rating is related to the overall level of credit risk of a firm, firms with lower credit ratings are expected to have higher CDS spreads, and to experience more abrupt changes in CDS spreads. In contrast, firms with higher credit ratings typically have lower and smoother CDS spreads over time. This intuition motivates us to partition our sample firms by credit rating.

[16]Specifically, we use the credit rating of the senior unsecured debt of the firm. Furthermore, this is the "instantaneous" credit rating at the end of 2004 and not the mean rating over the sample period, as only the former is available in our CDS dataset.

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. We partition our sample into four subgroups: AA and above, A, BBB, and BB and below. The majority of our sample firms are rated BBB, while about 17 percent of the firms are rated speculative-grade (BB and below).

[Insert Table 7 here.]

Table 7 reports time-series regression results partitioned by credit rating. Broadly speaking, the evidence shows that firms with lower credit ratings are more sensitive to many of the firm-level and market-level variables. In particular, the size of the average implied volatility coefficient and its average t-statistics are both increasing as the credit quality of the firm declines. Specifically, the average coefficients for implied volatility among the four subgroups are 0.77, 1.95, 2.81, and 6.39, respectively. The associated average t-statistics are 2.52, 3.90, 4.59, and 5.37, respectively. In contrast, the average historical volatility coefficient and t-statistics show no obvious pattern. Based on the significance of implied volatility across the four rating subgroups, we conclude that options market information is particularly useful in determining CDS spreads for firms with lower credit ratings.

4 Pricing Analysis

To more effectively address the nonlinear dependence of the CDS spread on its determinants, in this section we conduct a pricing analysis using a structural credit risk model whose equity volatility input can be chosen as either the historical or the implied volatility. For this pricing analysis we use the CreditGrades model, an industry benchmark jointly developed by RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank. This section begins with a brief introduction to the model. Although a full menu of extensions have been developed following the basic structural model of Merton (1974), we choose this industry model for two reasons. First, it appears to be widely used by practitioners.[17] Second, it contains an element of uncertain recovery rates, which helps to generate realistic short-term

[17]See Currie and Morris (2002).

credit spreads. Our analysis can be applied to other structural models in a straightforward manner, which we leave to future research.

4.1 The Model

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

$$\frac{dV_t}{V_t} = \sigma dW_t, \tag{4}$$

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

$$L = \overline{L}e^{\lambda Z - \lambda^2/2}, \tag{5}$$

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:[18]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{6}$$

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

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

[18]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.

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

$$c = -\frac{(1-R)\int_0^T e^{-rs} dq(s)}{\int_0^T e^{-rs} q(s)\, ds}. \tag{7}$$

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

$$c(0,T) = r(1-R)\frac{1-q(0)+H(T)}{q(0)-q(T)e^{-rT}-H(T)}, \tag{8}$$

where

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

Normally, the equity value S as a function of firm value V is needed to relate asset volatility σ to a more easily measurable equity volatility σ_S. Instead of using the full formula for equity value, CreditGrades uses a linear approximation $V = S + \overline{L}D$ to arrive at

$$\sigma = \sigma_S \frac{S}{S+\overline{L}D}. \tag{9}$$

This completely specifies the CreditGrades model. In summary, the 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.

4.2 Estimation Procedure

Out of the above eight inputs to the CreditGrades model, three are unobserved. They are the average default threshold $\overline{L}$, the default threshold uncertainty λ, and the bond recovery rate R. Hence the CreditGrades pricing formula can be abbreviated as

$$CDS_t = f\left(S_t, D_t, r_t, \sigma_t, T-t; \overline{L}, \lambda, R\right). \tag{10}$$

For the in-sample part of the pricing analysis, we take the entire sample period for each firm (say, of length N) to estimate these parameters by minimizing the sum of squared percentage pricing errors. 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 errors:

$$SSE = \min_{\overline{L},\lambda,R} \sum_{i=1}^{N} \left(\frac{\widehat{CDS}_i - CDS_i}{CDS_i} \right)^2 . \tag{11}$$

We also conduct an out-of-sample pricing analysis in which we estimate the three model parameters each day using the past n daily CDS spread observations, where $n = 25$, 126, or 252. We use the estimated parameters on day t with the equity price, debt per share, interest rate, and equity volatility observed on day $t+1$ to compute a predicted CDS spread for day $t+1$. Therefore, while the parameters $\left(\overline{L}, \lambda, R\right)$ are used "out-of-sample," the other inputs to the model, (S, D, r, σ_S), are always kept up to date. This is what we mean by "one-day-ahead forecast" of the CDS spread in the out-of-sample pricing analysis.

4.3 Estimation Results

Table 8 presents the in-sample estimation results using historical or implied volatilities as inputs. First, note that the cross-sectional averages of the parameters are similar for both sets of estimations. In the case of historical volatility-based estimation, 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 JP Morgan. These values are reasonably close to the cross-sectional average parameter estimates presented here.

[Insert Table 8 here.]

Table 8 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.[19] Generally, the

[19]Note that it is the sum of squared percentage 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.

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. Similarly, the implied volatility-based percentage RMSE is 0.46, while the historical volatility-based percentage RMSE is 0.50. As in our regression-based analysis, we split the sample firms into three groups according to their sample CDS spread volatility. We observe that the implied volatility yields significantly smaller pricing errors only among the most volatile group of firms, while there is virtually no difference among the other two groups.

To more carefully examine the balance between historical and implied volatility-based pricing errors, we construct a pricing error ratio (Ratio_RMSE) that is equal to the implied volatility-based in-sample percentage RMSE divided by the historical volatility-based in-sample percentage RMSE. This ratio varies substantially in the cross-section, with a mean value of 0.97. This observation suggests that while implied volatility yields somewhat 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, we conduct cross-sectional regressions with Ratio_RMSE as the dependent variable. For the independent variables, we use CDS spread volatility, option volume, option open interest, and other control variables such as credit rating, leverage ratio, and total assets.

[Insert Table 9 here.]

Table 9 presents the regression results. We find Ratio_RMSE to be smaller for obligors with lower ratings and higher CDS spread volatility. Additionally, the total assets is significant with a negative sign, the option open interest is marginally significant with a negative sign, and the option-stock volume ratio appears to be insignificant. To put these coefficients (in Regression Three) into perspective, consider the mean value of Ratio_RMSE at 0.97. A one-standard-deviation increase in the CDS spread volatility would lower it to 0.90. A one-standard-deviation increase in the option open interest would lower it further to

0.82. Lower the credit rating by one standard deviation reduces Ratio_RMSE still to 0.72. It appears that for firms with higher CDS spread volatility, higher option open interest, and lower credit rating, the implied volatility is especially informative for explaining CDS spreads, resulting in substantially smaller structural model pricing errors compared to when historical volatility is used in the same calibration. This result is broadly consistent with our regression findings in Section 3.

We also conduct an out-of-sample pricing analysis using the estimation method outlined in Section 4.2 to generate one-day-ahead CDS spread forecasts. This allows us to compute implied volatility- or historical volatility-based out-of-sample pricing errors. A cross-sectional analysis using the ratio of these pricing errors produces results similar to our in-sample pricing error analysis, and is therefore omitted.

5 Historical Volatilities with Alternative Horizons

Thus 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. In particular, we are interested in the trade-off between long-dated estimators, which are attractive because of their ability to produce stable asset volatility estimates, and short-dated estimators, which arguably could contain more timely market information. Specifically, we reproduce previous regression and pricing results using 22-, 63-, 126-, and 1,000-day historical volatility estimators.

[Insert Table 10 here.]

In Table 10, we present the benchmark regression of Table 4 using different historical volatility estimators. We notice that the implied volatility coefficient remains quite stable in its size as well as statistical significance. More interestingly, the historical volatility coefficient is not statistically significant for long-dated estimators such as the 1,000-day or the 252-day historical volatility, but becomes significant as the estimation horizon shrinks to 126 days and 63 days. Then, as the estimation horizon shrinks to just 22 days, it once again loses its significance. While shorter-horizon historical volatility estimators appear to have some explanatory power for CDS spreads, we note that the size of their coefficients is still much smaller than the size of the implied volatility coefficient. For example, when we use the 63-day historical volatility in the benchmark regressions, its average coefficient is only 0.83, while the average implied volatility coefficient is 2.46.

[Insert Table 11 here.]

In Table 11, we repeat the in-sample pricing exercise of Table 8 with different historical volatility estimators. 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 average pricing errors. 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.[20]

[Insert Table 12 here.]

When we conduct the cross-sectional pricing error analysis in Table 12, we find that the results closely resemble those in Table 9. Namely, the Ratio_RMSE variable is lower with higher CDS spread volatilities, higher option open interest, higher total assets, and lower credit ratings. Therefore, 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.

What do we make of these additional findings? Clearly, long-horizon historical volatilities are too smooth to reflect changes in the credit market condition in a timely manner. While they may lead to a good fit to the observed CDS spread in a quiet period, they miss

[20]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.

out on important credit events that are reflected in CDS spreads. On the other hand, short-horizon historical volatilities are more attuned to the market, but they are far too noisy to yield any improvement over the information content of implied volatility. We therefore conclude that the information advantage of implied volatility is robust to historical volatility estimators of different horizons.

6 Better Predictor of Future Volatility or Volatility Risk Premium?

Given the common perception of implied volatility as a "market consensus forecast" of future volatility, perhaps it comes as no surprise that implied volatility explains CDS spreads best in a volatile market. While it is certainly true that historical volatility, being a moving average, reacts slowly to new information, it is not at all clear that implied volatility is a superior predictor of future volatility in the setting of individual stocks. Jorion (1995), for example, points to measurement errors and transaction costs as a way to reconcile the dramatically different findings in different markets (e.g., FX vs. equity index). Because the liquidity of individual stock options is typically less than that of index options, whether implied volatility can predict future volatility of individual stocks is itself an interesting question.[21]

Separately, it is generally held that the difference between implied volatility and the expected future volatility is attributed to a volatility risk premium. For instance, the typical "volatility arbitrage" sells option straddles and profits from the difference between implied and realized volatility that is positive on average. Even if we had found the best forecast of future volatility, it is conceivable that implied volatility still has incremental explanatory power for the time-variation of CDS spreads because of its volatility risk premium component. In this section we explore the source of the CDS-IV relation along these lines.

[21] Studies based on stock index options, such as Canina and Figlewski (1993) and Day and Lewis (1992), generally do not support implied volatility as an informationally efficient estimator of future volatility. Lamoureux and Lastrapes (1993) find that individual stock option-implied volatility does not subsume the information contained in historical or GARCH volatility. However, their sample is limited to a small cross-section of 10 stocks.

First, we follow the literature to regress future realized volatility on implied and historical volatility for each obligor in our sample. Both historical and future realized volatility are computed over 252 trading days. We use daily data for the regression with the Newey and West (1987) correction to the standard errors for autocorrection and heteroskedasticity.[22]

[Insert Table 13 here.]

Our results can be found in Table 13. In univariate regressions, both historical volatility and implied volatility contain information for future realized volatility. However, with both included in the regression, implied volatility appears to dominate historical volatility in predicting future realized volatility. For example, the coefficient on implied volatility (β_2) is significant for 72 percent of the obligors, as opposed to only 49 percent for historical volatility (β_1). Similarly, in 47 percent of the cases we can reject the hypothesis of $\beta_1 = \beta_2$ in favor of $\beta_2 > \beta_1$, but in only 24 percent of the cases do we get the opposite result.

The size of the implied volatility coefficient is on average positive but less than unity (0.38). The intercept is on average positive (16.48). This suggests that implied volatility is a biased estimator for future volatility: when implied volatility is high, it needs to be scaled down; when it is low, it needs to be brought up toward the intercept. This finding is similar to Jorion (1995)'s results on implied volatility in the foreign currency futures options market.

Next, we study the effect of a time-varying volatility risk premium on CDS spreads. If we had identified a good estimator of future volatility, then the difference between implied volatility and this estimator can be interpreted as the volatility risk premium. Without having to identify this estimator, however, we can simply regress the CDS spread on future volatility (FV) and the difference between implied and future volatility ($IV - FV$), with the latter being interpreted as the volatility risk premium. If the volatility risk premium remains significant even in the presence of FV in this regression, we know that its effect on CDS spreads will not be subsumed by a volatility forecast, no matter how good the forecast

[22] Canina and Figlewski (1993) and Jorion (1995) use a similar correction to address the problem with volatilities measured on overlapping periods.

is.

[Insert Table 14 here.]

Table 14 shows the results of this regression. Compared to the benchmark regression results in Table 4, we see that the R^2 is slightly higher here. This is not surprising because we include future volatility in lieu of historical volatility in this regression. Also, the coefficient on FV is on average highly significant, in contrast to the lack of significance for the coefficient on HV in Table 4. This is evidence of a tight relation between CDS spread and volatility, given the right volatility estimator. Most notably in Table 14, however, is that $IV - FV$ remains highly significant in the presence of FV. Therefore, to model the CDS spread properly, we need to 1) have a good description of the behavior of volatility under the objective measure, and 2) incorporate the time-varying volatility risk premium. Our evidence suggests that each of these holds its own when it comes to explaining CDS spreads.

7 Conclusion

Which volatility measure, historical or option-implied volatility, is more useful for explaining credit default swap spreads? How does the informativeness of these volatility measures vary in the cross-section? What is the role of the volatility risk premium in the relation between CDS spreads and implied volatility? These are some of the questions that we address in this paper. Our motivation comes mainly from two sources. First, there is a growing academic literature highlighting the information content of equity options for predicting returns in the underlying stock market. The natural extension of this idea is that options market information, such as implied volatility, can be useful for explaining CDS spreads. Second, anecdotal evidence from the industry suggests that when the recent accounting scandals sent the CDS spreads of the perpetrators soaring, practitioners had to rely on option-implied volatility to calibrate their credit risk models.

Using firm-level time-series CDS spread regressions as well as pricing analyses, we find that implied volatility generally dominates historical volatility in explaining CDS spreads.

Moreover, the informativeness of implied volatility is particularly high among a subset of the firms. Specifically, the implied volatility coefficient in the CDS spread regressions becomes larger and more significant for firms with more volatile CDS spreads, larger option volume and option interest, and lower credit rating. In our pricing analysis, the ratio between the in-sample RMSE with implied volatility and the in-sample RMSE with historical volatility is lower for precisely these firms in a cross-sectional regression analysis of the pricing residuals. Our findings remain robust to historical volatilities of alternative estimation horizons, and persist in an out-of-sample pricing analysis.

Finally, our analysis shows implied volatility to be an informative but biased estimator of future stock return volatility. For the majority of the obligors, implied volatility dominates historical volatility in predicting future volatility. Although having a good estimator of future volatility is essential, the volatility risk premium embedded in option prices also makes an important contribution toward explaining CDS spreads.

References

[1] Acharya, V., T. Johnson, 2005, Insider trading in credit derivatives, Working paper, London Business School, forthcoming in *Journal of Financial Economics.*

[2] Amin, K., V. Ng, 1997, Inferring future volatility from the information in implied volatility in Eurodollar options: A new approach, *Review of Financial Studies* 10, 333-367.

[3] Avramov, D., G. Jostova, and A. Philipov, 2004, Credit risk changes: Common factors and firm-level fundamentals, Working paper, University of Maryland.

[4] Bakshi, G., and N. Kapadia, 2003, Volatility risk premium embedded in individual equity options: Some new insights, *Journal of Derivatives* 11(1), 45-54.

[5] Bates, D., 2003, Empirical option pricing: A retrospection, *Journal of Econometrics* 116, 387-404.

[6] Black, F., and J. Cox, 1976, Valuing corporate securities: Some effects of bond indenture provisions, *Journal of Finance* 31, 351-367.

[7] Blanco, R., S. Brennan, and I. W. Marsh, 2005, An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps, *Journal of Finance* 60, 2255-2281.

[8] Bollerslev, T., M. Gibson, and H. Zhou, 2006, Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities, Working paper, Federal Reserve Board.

[9] Campbell, J., and G. Taksler, 2003, Equity volatility and corporate bond yields, *Journal of Finance* 58, 2321-2349.

[10] Canina, L., and S. Figlewski, 1993, The informational content of implied volatility, *Review of Financial Studies* 6, 659-681.

[11] Cao, C., Z. Chen, and J. Griffin, 2005, Informational content of option volume prior to takeovers, *Journal of Business* 78, 1073-1109.

[12] Chernov, M., 2002, On the role of risk premia in volatility forecasting, Working paper, Columbia University, forthcoming in *Journal of Business and Economic Statistics*.

[13] Christensen, B. J., and N. R. Prabhala, 1998, The relation between implied and realized volatility, *Journal of Financial Economics* 50, 125-150.

[14] Collin-Dufresne, P., R. Goldstein, and J. S. Martin, 2001, The determinants of credit spread changes, *Journal of Finance* 56, 2177-2207.

[15] CreditGrade Technical Document, 2002, http://www.creditgrades.com/resources/pdf/CGtechdoc.pdf.

[16] Cremers, M., J. Driessen, P. Maenhout, and D. Weinbaum, 2004, Individual stock option prices and credit spreads, Working paper, Yale University.

[17] Currie, A., and J. Morris, 2002, And now for capital structure arbitrage, *Euromoney*, December, 38-43.

[18] Day, T., and C. Lewis, 1992, Stock market volatility and the information content of stock index options, *Journal of Econometrics* 52, 267-287.

[19] Donaldson, R. G., and M. J. Kamstra, 2005, Volatility forecasts, trading volumes, and the ARCH versus option-implied volatility trade-off, *Journal of Financial Research* 28, 519-538.

[20] Duarte, J., F. A. Longstaff, and F. Yu, 2005, Risk and return in fixed income arbitrage: Nickels in front of a steamroller? Working paper, UCLA, forthcoming in *Review of Financial Studies*.

[21] Duffee, D., 1998, The relation between Treasury yields and corporate bond yield spreads, *Journal of Finance* 53, 2225-2241.

[22] Easley, D., M. O'Hara, and P. Srinivas, 1998, Option volume and stock prices: Evidence on where informed traders trade, *Journal of Finance* 53, 431-465.

[23] Ericsson, J., K. Jacobs, and R. Oviedo-Helfenberger, 2004, The determinants of credit default swap premia, Working paper, McGill University.

[24] Hull, J., M. Predescu, and A. White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking and Finance* 28, 2789-2811.

[25] Jorion, P., 1995, Predicting volatility in the foreign exchange market, *Journal of Finance* 50, 507-528.

[26] Lamoureux, C., and W. Lastrapes, 1993, Forecasting stock-return variance: Toward an understanding of stochastic implied volatility, *Review of Financial Studies* 6, 293-326.

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

[28] Merton, R., 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449-470.

[29] Newey, W., and K. West, 1987, A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

[30] Pan, J., and A. Poteshman, 2006, The information in option volume for future stock prices, *Review of Financial Studies* 19, 871-908.

[31] Yu, F., 2006, How profitable is capital structure arbitrage? *Financial Analysts Journal* 62(5), 47-62.

[32] Zhang, B. Y., H. Zhou, and H. Zhu, 2005, Explaining credit default swap spreads with equity volatility and jump risks of individual firms, Working paper, Moody's KMV.

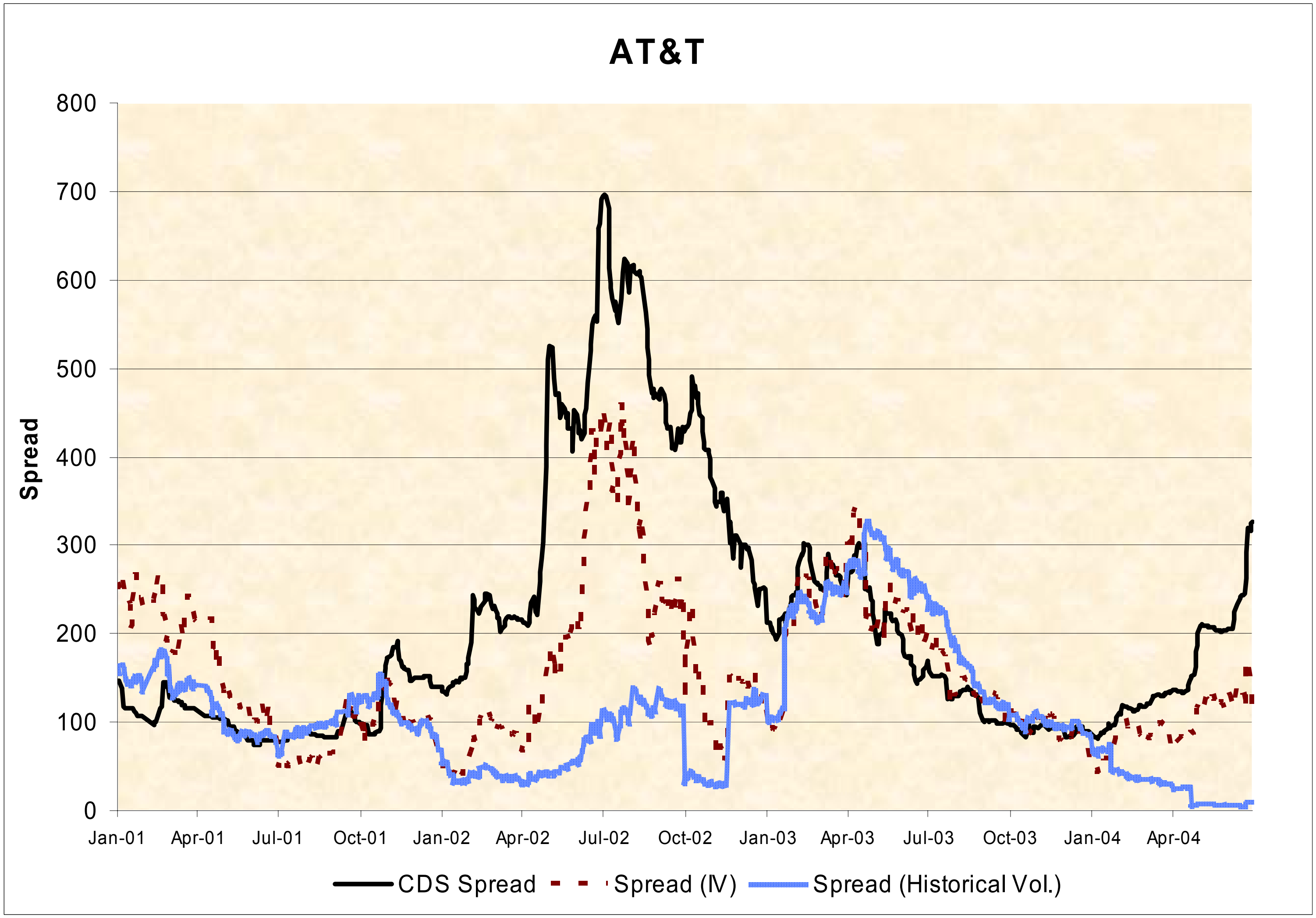

Figure 1. AT&T CDS Spreads

CDS Spread is market CDS spread. Spread (IV) is the spread computed using option-implied volatility and the CreditGrades model. Spread (Historical Vol.) is the spread computed using 252-day historical volatility and the CreditGrades model.

Table 1. Summary Statistics

For each variable, Panel A reports the cross-sectional summary statistics of the time-series means of 220 sample firms. Panel B reports the summary statistics of market variables. 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 nonzero open interests; Implied Volatility Skew is the difference between the implied volatilities of OTM and ATM puts divided by the difference in the strike-to-spot ratios; Leverage Ratio is the ratio of total liability over the sum of total liability and market capitalization; Firm Stock Return is the 252-day average of firm stock returns; Market Capitalization is the product of the stock price and shares outstanding; Market Historical Volatility is the 252-day historical volatility of the S&P500 index returns; Market Implied Volatility is the 30-day standardized ATM implied volatility of S&P100 put options; Market Implied Volatility Skew is the implied volatility skew of S&P100 index put option; Market Return is the 252-day average of S&P500 index returns; Treasure Rate is the five-year US Treasury constant maturity yield; Yield Curve Slope is the difference between ten-year and two-year US Treasury yields; Bond Liquidity is the difference between ten-year swap and ten-year US Treasury yields; Baa Rate is the average yield of U.S. corporate bonds rated Baa by Moody's. The sample period extends from January 2001 through June 2004.

Panel A: Firm-Level Variables

	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
Implied Volatility Skew	0.55	0.46	0.52	0.60	0.17
Leverage Ratio (%)	45.80	33.70	46.89	59.65	19.40
Firm Stock Return (%)	20.99	8.39	17.85	29.08	19.32
Market Capitalization ($billion)	20.88	3.54	9.22	19.04	37.30

Panel B: Market-Level Variables

	Mean	Q1	Median	Q3	Standard Deviation
Market Historical Volatility (%)	21.48	18.89	21.97	24.14	4.01
Market Implied Volatility (%)	23.22	18.47	21.77	28.11	6.73
Market Implied Volatility Skew	1.13	0.69	0.88	1.23	0.80
Market Return (%)	-2.30	-16.90	-10.19	15.58	19.07
Treasury Rate (%)	3.71	3.04	3.55	4.49	0.79
Yield Curve Slope (%)	1.90	1.80	2.05	2.30	0.57
Bond Liquidity (%)	0.55	0.40	0.51	0.70	0.19
Baa Rate (%)	7.36	6.75	7.56	7.95	0.65

Table 2. Sample Properties of Equity Options

The reported numbers are, respectively, the cross-sectional averages of the number of option contracts and the percentage of the number of option contracts (in parentheses) for each moneyness and maturity category. Moneyness is defined as the ratio of spot price divided by strike price for calls and strike price divided by spot price for puts. Maturity is the number of days to expiration. The sample period extends from January 2001 through June 2004 for a total of 51,233 calls and puts for the 220 sample firms with options listed on all U.S. option markets.

Panel A: All Contracts

Maturity \ Moneyness	< 0.8	0.8 - 1.0	1.0 -1.2	>1.2	Subtotal
< 30 days	2036 (3.67)	2640 (5.66)	2246 (4.85)	2416 (4.45)	9338 (18.63)
31 - 90 days	3519 (6.28)	4526 (9.69)	3853 (8.29)	4168 (7.63)	16066 (31.89)
91 -180 days	3184 (5.68)	3659 (7.77)	3095 (6.61)	3729 (6.80)	13667 (26.86)
>180 days	2976 (4.95)	3113 (6.37)	2649 (5.47)	3424 (5.82)	12162 (22.62)
Subtotal	11715 (20.58)	13938 (29.50)	11842 (25.22)	13737 (24.70)	51233 (100.00)

Panel B: Contracts with Volume

Maturity \ Moneyness	< 0.8	0.8 -1.0	1.0 -1.2	>1.2	Subtotal
< 30 days	179 (0.85)	1197 (9.50)	1017 (8.37)	307 (1.64)	2700 (20.36)
31 - 90 days	481 (2.33)	2248 (18.15)	1396 (10.72)	430 (2.20)	4555 (33.40)
91 -180 days	640 (3.19)	1847 (15.27)	932 (7.00)	386 (1.95)	3806 (27.41)
>180 days	678 (3.08)	1354 (9.82)	648 (4.22)	387 (1.72)	3067 (18.84)
Subtotal	1979 (9.44)	6646 (52.73)	3993 (30.31)	1510 (7.52)	14128 (100.00)

Panel C: Contracts with Open Interest

Maturity \ Moneyness	< 0.8	0.8 -1.0	1.0 -1.2	>1.2	Subtotal
< 30 days	1431 (3.24)	2377 (6.64)	1944 (5.36)	1485 (3.25)	7237 (18.49)
31 - 90 days	2572 (5.88)	3871 (10.68)	2951 (7.96)	2498 (5.55)	11893 (30.07)
91 -180 days	2789 (6.28)	3540 (10.08)	2761 (7.65)	2676 (5.86)	11765 (29.87)
>180 days	2549 (5.12)	2705 (6.96)	1960 (4.83)	2375 (4.66)	9589 (21.57)
Subtotal	9341 (20.52)	12493 (34.36)	9616 (25.80)	9034 (19.32)	40484 (100.00)

Panel D: Contracts with Open Interest – Put only

Maturity \ Moneyness	< 0.8	0.8 -1.0	1.0 -1.2	>1.2	Subtotal
< 30 days	745 (3.68)	1171 (6.81)	951 (5.34)	653 (2.80)	3520 (18.63)
31 - 90 days	1312 (6.63)	1862 (10.65)	1434 (7.84)	1139 (4.89)	5747 (30.01)
91 -180 days	1348 (6.70)	1705 (10.15)	1362 (7.68)	1313 (5.53)	5727 (30.06)
>180 days	1186 (5.21)	1247 (6.59)	976 (4.82)	1226 (4.68)	4636 (21.30)
Subtotal	4590 (22.22)	5985 (34.20)	4722 (25.68)	4332 (17.90)	19630 (100.00)

Table 3. Two-Step Time-Series Regression Test

Cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for 220 sample firms. For each firm, we conduct the following two-step time-series regression test. In Step 1, we regress the daily CDS spread on historical volatility. In Step 2, we regress the residual from Step 1 on option implied volatility. In Panel B, we reverse the role of historical volatility and implied volatility and repeat each regression. Newey and West (1987) standard errors (5 lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

Panel A	First Step	Second Step
	$CDS_t = \alpha_0 + \alpha_1 HV_t + \varepsilon_t$	$\varepsilon_t = \beta_0 + \beta_1 IV_t + \eta_t$
Intercept	-36.71	-135.71
	(-2.73)	(-6.93)
Historical Volatility	4.14	
	(12.46)	
Implied Volatility		2.97
		(6.72)
Adjusted R^2	36%	23%
Percentage of t's ≥ 1.96 (Volatility)	92%	91%

Panel B	First Step	Second Step
	$CDS_t = \alpha_0 + \alpha_1 IV_t + \varepsilon_t$	$\varepsilon_t = \beta_0 + \beta_1 HV_t + \eta_t$
Intercept	-101.56	-27.90
	(-5.91)	(-1.73)
Historical Volatility		0.71
		(1.53)
Implied Volatility	5.64	
	(15.88)	
Adjusted R^2	56 %	9%
Percentage of t's ≥ 1.96 (Volatility)	99%	45%

Table 4. Time-Series Regression Analysis of CDS Spreads

Cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for 220 sample firms. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	1	2	3	4
Intercept	-121.73	-189.29	-194.70	-248.49
	(-7.58)	(-2.97)	(-2.82)	(-3.14)
Historical Volatility (β_1)	1.25	1.19	1.56	0.97
	(2.56)	(1.81)	(2.50)	(1.26)
Implied Volatility (β_2)	4.92	3.71	3.53	3.07
	(10.51)	(7.89)	(5.59)	(4.41)
Additional Firm Specific Variables				
Implied Volatility Skew		9.48	8.55	5.35
		(0.93)	(1.18)	(0.77)
Leverage Ratio		1.48	1.55	1.58
		(0.98)	(1.03)	(0.95)
Firm Stock Return		-0.03	0.02	0.01
		(-0.35)	(0.02)	(0.34)
Market Volatility Variables				
Market Historical Volatility			-0.37	0.71
			(-1.05)	(-0.01)
Market Implied Volatility			-0.27	-0.84
			(0.11)	(0.85)
Market Implied Volatility Skew			0.45	0.00
			(0.26)	(0.06)
Macro Variables				
Market Return				0.06
				(0.27)
Treasury Rate				-8.99
				(-1.54)
Yield Curve Slope				-2.90
				(-1.17)
Bond Liquidity				26.80
				(1.14)
Baa Rate				17.52
				(2.69)
Adjusted R^2	63%	74%	79%	85%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	54%	47%	50%	44%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)	94%	87%	79%	73%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)	70%	64%	47%	46%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)	14%	14%	26%	23%

Table 5. Time-Series Regression Analysis of CDS Spreads Partitioned by CDS Spread Volatility

This table reports the cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for the three sub-groups partitioned by the volatility of CDS spreads. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	Group1 (Least volatile)	Group2	Group3 (Most volatile)
Intercept	-33.11	-168.99	-544.46
	(-1.72)	(-3.91)	(-3.77)
Historical Volatility (β_1)	0.26	1.63	1.02
	(0.66)	(2.17)	(0.93)
Implied Volatility (β_2)	0.81	1.77	6.65
	(3.17)	(3.85)	(6.23)
Additional Firm Specific Variables			
Implied Volatility Skew	0.43	2.75	12.90
	(0.35)	(0.73)	(1.24)
Leverage Ratio	-0.06	0.93	3.89
	(0.10)	(1.34)	(1.40)
Firm Stock Return	0.01	0.01	0.02
	(0.42)	(0.26)	(0.36)
Market Volatility Variables			
Market Historical Volatility	-0.04	-0.88	3.09
	(-0.08)	(-0.98)	(1.05)
Market Implied Volatility	-0.12	-0.43	-1.96
	(-0.45)	(-1.09)	(-1.01)
Market Implied Volatility Skew	0.01	0.49	-0.50
	(-0.03)	(0.34)	(-0.14)
Macro Variables			
Market Return	0.00	0.13	0.06
	(0.08)	(0.58)	(0.14)
Treasury Rate	-4.22	-9.68	-13.05
	(-1.74)	(-1.75)	(-1.13)
Yield Curve Slope	-3.97	-13.23	8.64
	(-1.53)	(-2.13)	(0.16)
Bond Liquidity	7.19	23.79	49.47
	(1.01)	(1.29)	(1.12)
Baa Rate	8.54	21.02	22.93
	(2.98)	(3.22)	(1.87)
Adjusted R^2	81%	85%	89%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	38%	57%	37%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)	64%	74%	79%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)	42%	38%	59%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)	25%	30%	15%
Number of Firms	73	74	73

Table 6. Time-Series Regression Analysis of CDS Spreads Partitioned by Option Volume

This table reports the cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for the three sub-groups partitioned by option volume (standardized by stock volume). For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	Group1 (Smallest)	Group2	Group3 (Largest)
Intercept	-204.71	-247.64	-293.13
	(-3.23)	(-2.66)	(-3.53)
Historical Volatility (β_1)	1.02	1.14	0.75
	(1.40)	(1.21)	(1.17)
Implied Volatility (β_2)	2.33	2.60	4.29
	(3.37)	(3.90)	(5.99)
Additional Firm Specific Variables			
Implied Volatility Skew	1.34	5.81	8.89
	(0.31)	(0.85)	(1.16)
Leverage Ratio	1.29	1.01	2.46
	(0.88)	(0.56)	(1.40)
Firm Stock Return	0.15	-0.12	0.01
	(1.32)	(-0.41)	(0.13)
Market Volatility Variables			
Market Historical Volatility	1.06	1.06	0.02
	(0.45)	(0.16)	(-0.64)
Market Implied Volatility	-0.23	-0.77	-1.52
	(-0.28)	(-1.12)	(-1.15)
Market Implied Volatility Skew	0.28	-0.13	-0.15
	(0.27)	(-0.13)	(0.03)
Macro Variables			
Market Return	0.09	0.09	0.01
	(-0.18)	(0.47)	(0.52)
Treasury Rate	-6.72	-13.09	-7.10
	(-1.27)	(-1.72)	(-1.63)
Yield Curve Slope	-8.52	-5.26	5.12
	(-1.71)	(-1.25)	(-0.56)
Bond Liquidity	36.06	17.10	27.38
	(1.37)	(1.01)	(1.05)
Baa Rate	17.02	24.73	10.70
	(2.78)	(2.66)	(2.63)
Adjusted R^2	86%	84%	86%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	42%	45%	45%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)	66%	73%	79%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)	42%	43%	53%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)	30%	20%	19%
Number of Firms	73	74	73

Table 7. Time-Series Regression Analysis of CDS Spreads Partitioned by Credit Rating

This table reports the cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for the four sub-groups partitioned by credit rating. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	AA and above	A	BBB	BB and below
Intercept	-60.83	-81.33	-245.84	-584.24
	(-1.13)	(-2.24)	(-3.69)	(-3.66)
Historical Volatility (β_1)	0.54	0.21	1.32	1.33
	(1.79)	(0.64)	(1.67)	(0.87)
Implied Volatility (β_2)	0.77	1.95	2.81	6.39
	(2.52)	(3.90)	(4.59)	(5.37)
Additional Firm Specific Variables				
Implied Volatility Skew	1.66	1.86	4.17	15.51
	(1.48)	(0.47)	(0.70)	(1.21)
Leverage Ratio	0.32	-0.29	1.29	5.81
	(-1.03)	(-0.12)	(1.21)	(2.56)
Firm Stock Return	0.05	-0.02	0.04	-0.03
	(0.23)	(0.01)	(0.56)	(0.29)
Market Volatility Variables				
Market Historical Volatility	0.61	-0.25	-0.15	4.75
	(-0.14)	(-0.26)	(-0.33)	(1.34)
Market Implied Volatility	-0.11	-0.20	-0.43	-3.25
	(0.21)	(-0.75)	(-0.75)	(-1.65)
Market Implied Volatility Skew	-0.05	0.21	0.18	-0.81
	(-0.17)	(0.11)	(0.11)	(-0.10)
Macro Variables				
Market Return	0.06	0.08	0.01	0.17
	(0.47)	(0.52)	(0.10)	(0.27)
Treasury Rate	3.77	-6.22	-13.62	-4.45
	(-0.88)	(-1.78)	(-1.69)	(-0.97)
Yield Curve Slope	9.47	-6.79	-12.08	25.34
	(-1.07)	(-1.53)	(-1.80)	(1.15)
Bond Liquidity	16.84	12.46	27.39	51.18
	(1.24)	(1.09)	(1.16)	(1.13)
Baa Rate	-2.70	13.52	24.73	10.04
	(2.60)	(3.16)	(2.84)	(1.56)
Adjusted R^2	83%	82%	87%	86%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	62%	38%	50%	32%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)	62%	70%	75%	74%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)	38%	47%	44%	55%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)	38%	22%	27%	11%
Number of Firms	13	60	109	38

Table 8. Properties of Estimated Parameters and In-Sample Pricing Errors

Panel A reports the cross-sectional averages and standard errors of estimated parameters and in-sample pricing errors for 220 sample firms. The CreditGrades model is estimated where either option-implied volatility or 252-day historical volatility is used as an input. $\bar{L}$ 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 the root-mean-squared-errors (RMSE). Panel B reports the cross-sectional averages of in-sample pricing errors for 220 sample firms partitioned by CDS volatility.

Panel A In-sample Estimated Parameters and Pricing Errors

	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

Panel B In-sample Pricing Errors Partitioned by CDS Volatility

	Group1 (Least volatile)		Group2		Group3 (Most volatile)	
	IV	Hist. Vol.	IV	Hist. Vol.	IV	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 9. 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 in-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. Coefficients with *p*-values less than 0.05 are marked with an asterisk.

	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 Asset (/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%

Table 10. Time-Series Regression Analysis of CDS Spreads – Historical Volatilities of Alternative Horizons

Cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for 220 sample firms using historical volatility of alternative horizon. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	Historical Volatility				
	22-day	63-day	126-day	252-day	1000-day
Intercept	-232.20	-216.87	-190.15	-248.49	-363.21
	(-2.90)	(-2.77)	(-2.54)	(-3.14)	(-2.40)
Historical Volatility (β_1)	0.28	0.83	1.27	0.97	2.77
	(1.50)	(2.80)	(3.12)	(1.26)	(0.98)
Implied Volatility (β_2)	2.87	2.46	2.52	3.07	3.12
	(3.96)	(2.93)	(3.18)	(4.41)	(4.72)
Additional Firm Specific Variables					
Implied Volatility Skew	4.78	4.77	4.62	5.35	5.05
	(0.65)	(0.52)	(0.49)	(0.77)	(0.70)
Leverage Ratio	1.63	1.47	1.36	1.58	1.30
	(1.00)	(1.00)	(0.86)	(0.95)	(0.69)
Firm Stock Return	0.00	-0.02	-0.02	0.01	-0.02
	(-0.04)	(-0.13)	(-0.15)	(0.34)	(-0.16)
Market Volatility Variables					
Market Historical Volatility	1.87	1.57	0.65	0.71	1.53
	(0.86)	(0.50)	(-0.50)	(-0.01)	(0.40)
Market Implied Volatility	-0.93	-0.71	-0.59	-0.84	-0.80
	(-0.89)	(-0.49)	(-0.33)	(0.85)	(-0.88)
Market Implied Volatility Skew	-0.10	-0.15	-0.12	0.00	0.00
	(0.02)	(-0.02)	(-0.06)	(0.06)	(0.04)
Macro Variables					
Stock Market Return	0.04	-0.03	0.01	0.06	0.00
	(0.31)	(0.10)	(0.43)	(0.27)	(0.30)
Treasury Rate	-9.20	-5.73	-8.96	-8.99	-8.98
	(-1.41)	(-0.91)	(-1.44)	(-1.54)	(-1.36)
Yield Curve Slope	-6.27	-0.88	-3.18	-2.90	-10.83
	(-1.73)	(-1.24)	(-1.45)	(-1.17)	(-1.66)
Bond Liquidity	20.96	18.00	17.78	26.80	27.09
	(1.00)	(0.91)	(0.79)	(1.14)	(1.16)
Baa Rate	19.72	15.59	14.97	17.52	21.51
	(3.00)	(2.55)	(2.61)	(2.69)	(2.34)
Adjusted R^2	85%	85%	86%	85%	85%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	40%	60%	60%	44%	40%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)	67%	58%	59%	73%	75%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)	62%	45%	40%	46%	34%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)	4%	18%	27%	23%	30%

Table 11. Properties of Estimated Parameters and In-Sample Pricing Errors – Historical Volatilities of Alterative Horizons

This table reports the cross-sectional averages of estimated parameters and in-sample pricing errors of 220 sample firms. The CreditGrades model is estimated where either option-implied volatility or historical volatility (of alternative horizon) is used as an input. $\bar{L}$ 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 12. Cross-Sectional Regression Analysis of Structural Model Pricing Errors – Historical Volatilities of Alterative Horizons

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 in-sample 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. Coefficients with *p*-values less than 0.05 are marked with an asterisk.

	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 Asset (/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%

Table 13. Predictive Regression of Future Realized Volatility

Cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for 220 sample firms. For each firm and each time-series regression, the dependent variable is the future realized volatility (252-day). The definitions of independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	1	2	3
Intercept	22.23	14.70	16.48
	(8.58)	(6.73)	(6.05)
Historical Volatility (β_1)	0.32		0.08
	(9.59)		(1.48)
Implied Volatility (β_2)		0.49	0.38
		(10.16)	(4.51)
Adjusted R^2	26%	23%	36%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	70%		49%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)		85%	72%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)			47%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)			24%

Table 14. Time-Series Regression Analysis of CDS Spreads Using Future Realized Volatility and the Volatility Risk Premium

Cross-sectional averages of coefficients, t statistics (in parentheses), and adjusted R-squares of time-series regressions for 220 sample firms. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. Volatility risk premium is proxied by the difference between implied volatility and future realized volatility (252-day). The definitions of other independent variables are provided in Table 1. Newey and West (1987) standard errors (five lags) are used to compute t-statistics. The sample period extends from January 2001 through June 2004.

	1	2	3	4
Intercept	-116.03	-234.24	-235.62	-235.74
	(-7.93)	(-4.35)	(-4.18)	(-2.99)
Future Realized Volatility (β_1)	6.29	4.81	5.13	4.33
	(17.28)	(11.87)	(9.40)	(5.25)
Implied Volatility - Future Realized Volatility (β_2)	5.00	3.33	3.39	3.17
	(12.41)	(7.28)	(5.96)	(4.94)
Additional Firm Specific Variables				
Implied Volatility Skew		10.41	8.88	5.41
		(1.20)	(1.28)	(0.80)
Leverage Ratio		2.91	2.14	1.60
		(2.60)	(1.82)	(1.08)
Firm Stock Return		-0.07	-0.01	-0.03
		(-0.71)	(-0.18)	(-0.14)
Market Volatility Variables				
Market Historical Volatility			1.86	1.97
			(1.09)	(1.12)
Market Implied Volatility			-0.62	-0.89
			(-0.80)	(-1.03)
Market Implied Volatility Skew			0.36	-0.10
			(0.30)	(0.03)
Macro Variables				
Market Return				0.10
				(0.46)
Treasury Rate				-8.44
				(-1.43)
Yield Curve Slope				-4.01
				(-1.04)
Bond Liquidity				21.71
				(1.14)
Baa Rate				13.60
				(1.89)
Adjusted R^2	68%	77%	81%	86%
Percentage of t's ≥ 1.96 (β_1, FV)	97%	93%	91%	75%
Percentage of t's ≥ 1.96 (β_2, IV - FV)	96%	86%	85%	78%