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Abstract

We explore the connection between the market for single-name credit default swaps (CDS) and the market for individual stock options. We find that the contemporaneous link between CDS spreads and option-implied volatilities is stronger among firms with lower credit ratings, higher CDS spread volatilities, and more actively traded options. Among such firms, the changes in both CDS spreads and implied volatilities forecast future stock returns. Although the changes in implied volatility consistently forecast future CDS spread changes, the reverse does not hold. We interpret these findings as broadly consistent with informed traders preferentially using the options market, and to some extent the CDS market, to exploit their information advantage. Although implied volatility dominates historical volatility in forecasting the future realized volatility on individual stocks, the volatility risk premium embedded in option prices also plays a crucial role in explaining CDS spreads. Our results are robust under a pricing analysis using a structural credit risk model. They are also unaffected by historical volatilities estimated at short or long horizons.

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 (obligor), 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 volatility in the determination of bond and CDS spreads.[2] Following this literature, we conduct a comprehensive analysis of the relation between CDS spreads and equity volatilities. What distinguishes this study from the extant literature is our focus on the economic intuition behind the information content of option-implied volatility (IV) for credit default swap valuation.

First, consider the choices of an informed trader who seeks to exploit her private information regarding the credit risk of a firm. She could trade in a variety of different venues, such as the stock, bond, option, or CDS market. As pointed out by Black (1975), the leverage inherent in options makes them an attractive vehicle for informed trading. Moreover, Back (1993) shows that the presence of asymmetric information causes options to become non-redundant assets that can play an important role in price discovery. Putting these elements together, Easley, O'Hara, and Srinivas (1998) present a model in which an informed trader will use options if they have sufficient leverage and liquidity, or if the degree of information asymmetry in the market is high. Recent empirical studies, such as Pan and Poteshman (2006) and Cao, Chen, and Griffin (2005), have confirmed these theoretical conjectures by examining the predictive power of option volume for future stock returns.

On the other hand, credit default swaps share similar payoff characteristics with certain types of options (e.g., out-of-the-money puts) in that both offer a low cost and effective

[1] For details, see the most recent International Swaps and Derivatives Association (ISDA) Market Survey.

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

protection against downside risk. Therefore, all of the aforementioned arguments are also applicable to informed trading in the CDS market. Indeed, Acharya and Johnson (2005) have recently shown that changes in the CDS spread lead stock returns among obligors that have experienced an increase in credit risk. They also find that this lead-lag relation becomes stronger when more banks are lending to the obligor, alluding to banks as the insider in the CDS market.

If informed/insider trading is the common underpinning of price discovery in the option and CDS markets, then we should expect a contemporaneous link between CDS spreads and option-implied volatility. Furthermore, the strength of this relation should increase with option market liquidity and the degree of information asymmetry in the cross-section of obligors. To test this main hypothesis, we first 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.[3] We then divide the firms into sub-groups based on their CDS spread volatility, option trading volume and open interest, and credit rating. Overall, our regression results suggest that implied volatility dominates historical volatility in explaining the time-variation of CDS spreads. More importantly, we find that both the size and the statistical significance of the implied volatility coefficient are most pronounced for speculative-grade obligors with highly volatile CDS spreads and actively-traded options. To the extent that option volume and open interest are commonly-used measures of option market liquidity, and lower-rated and more volatile CDS obligors are associated with more informed/insider trading, these results are consistent with our main hypothesis.

Looking beyond the contemporaneous links, we also explore the lead-lag relation among the stock, option, and CDS markets. Following Acharya and Johnson (2005), we first estimate a residual component of the changes in CDS spread, implied volatility, and the stock price that contains information unique to each market. We then examine how each residual is reflected in subsequent movements in other markets. Intriguingly, we find that both the CDS and the implied volatility residuals are able to predict future stock returns among firms with lower credit ratings or higher CDS spread volatilities. Furthermore, while the implied volatility residual is able to forecast changes in the CDS spread, the opposite does not hold. Overall, our finding is consistent with informed traders preferentially using both option and CDS markets to exploit their information, which subsequently diffuses into

[3] 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.

the stock market.

Having explored the cross-sectional determinants of the CDS-IV relation, an important question regarding the nature of this relation nonetheless remains unanswered. Namely, is implied volatility able to explain CDS spreads because it forecasts future volatility better, or because it captures a volatility risk premium? Previous studies tend to focus on equity index options, and have produced mixed evidence on the first part of the question.[4] As for the second part of the question, the difference between the expected future volatility under the objective measure and implied volatility is commonly regarded as a volatility risk premium.[5] Because of the similarity between the payoffs of out-of-the-money puts and credit default swaps, this risk premium component can presumably help explain CDS spreads in a way that even the best volatility estimator cannot.

To fully address these questions, we first regress future realized volatility (FV) on implied and historical volatility for each sample firm. Generally, we find implied volatility to be an informative but biased 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.

We conduct two additional exercises to ensure the robustness of our findings. First, 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 information from either the options market or the equity market as input.[6] 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

[4] See Canina and Figlewski (1993), Christensen and Prabhala (1998), Day and Lewis (1992), and Lamoureux and Lastrapes (1993), among others.

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

[6] 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).

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. As a result, we minimize firm-level sum of squared pricing errors over the parameters of the CreditGrades model. We then 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 industry practice of calibrating structural models to implied volatility in a turbulent market.[7]

For the second robustness check, we repeat the regression and pricing analyses with 22-, 63-, 126-, and 1,000-day historical volatility estimators. We find that the information content of historical volatility for CDS spreads follows an inverse U-shaped pattern. Namely, the statistical significance of the historical volatility coefficient diminishes as the estimation horizon is either shortened or lengthened. While the 63-day and 126-day historical volatility coefficients are statistically significant, they are less than half the size of the implied volatility coefficient. Furthermore, the cross-sectional behavior of the pricing error ratio remains unchanged in all cases. These results suggest that the information advantage of implied volatility remains robust to historical volatility estimated at different horizons.

The rest of this paper is organized as follows. In Section 2, we document the major data sources and variables used in our study. In Section 3, we conduct a regression-based analysis of the contemporaneous relation between CDS spreads and implied and historical volatility. Section 4 then presents an analysis of the lead-lag relation among the stock, option, and CDS markets. Section 5 examines the role of the volatility risk premium in explaining the CDS spread. In Section 6, we conduct a pricing analysis of the relation between CDS spreads and the two volatility measures. We also present additional results using historical volatility estimators of alternative horizons. We conclude with Section 7.

[7] For example, while the CreditGrades Technical Document (2002) recommends the 1,000-day historical volatility as an input to the CreditGrades 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."

2 Data

2.1 Credit Default Swaps

As described in the introduction, the CDS spread is the premium paid to insure the loss of value on the underlying debt obligation against pre-specified credit events. As such, its value is directly determined by the probability of default along with the loss-given-default on the underlying obligation. Contrast this with the yield spread on corporate bonds, which is affected by the choice of the risk-free benchmark yield and the differential tax treatment and liquidity of corporate and Treasury bonds, the CDS spread is often perceived as a superior measure of default risk.[8]

Therefore, we collect single-name CDS spreads from a comprehensive database compiled by the Markit Group. This database provides daily CDS composite spreads on more than 2,400 individual obligors since 2001. The daily composite spreads are computed 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 calculated, ensuring a reasonable quality for the data.

For each obligor and each day, the composite spread is specified across the seniority of the underlying debt obligation and the currency and maturity of the contract. For our analysis, we use the composite spread of US dollar-denominated five-year CDS contracts written on senior unsecured debt of North American obligors. Although the maturity of the composite spread can range between six months to 30 years, 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. Similarly, the majority of the contracts are written on senior unsecured obligations.

CDS contracts also vary in the degree of restructuring permitted as part of the definition of credit events, ranging from no restructuring to full restructuring. Restructuring causes obligations with the same seniority to diverge in value. As a result, the embedded cheapest-to-deliver option can cause the CDS spread to increase. For North American obligors, the dominant type of CDS contract allows the so-called "modified restructuring," which restricts the range of maturities of debt instruments that can be delivered in a credit event. This is

[8] For example, Longstaff, Mithal, and Neis (2005) assume that the CDS spread is entirely attributed to default risk. Ericsson, Reneby, and Wang (2005) find that structual credit risk models generally underpredict bond yield spreads but do not underpredict CDS spreads.

the subset of CDS contracts used in our study.[9]

2.2 Equity Options

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 using interpolation. While it may appear convenient to use the standardized implied volatilities provided by OptionMetrics, we find that they are sensitive to the discrete maturity and moneyness effects. For example, the OptionMetrics 30-day at-the-money put-implied volatility is interpolated from four put options with strike prices straddling the 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 for the purpose of CDS valuation. The value of such options is most sensitive to the left tail of the risk-neutral stock return distribution, as is the CDS spread. However, some firms in our sample do not 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 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

[9] As shown by Berndt, Jarrow, and Kang (2006), the difference in CDS spreads across different types of restructuring risks amounts to about six to eight percent of the CDS spread on a non-restructuring contract. Because this appears to be a small effect, we continue to interpret the CDS spread as a measure of default risk.

spread.[10]

2.3 Other Firm-Level and Market-Level Variables

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 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 the intuition of 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.[11]

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

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

[11] 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).

at least one and a half years of daily data available for the firm-level time-series analysis. Combining all variables documented above, we arrive at a final sample of 220 firms.

Figure 2 shows the number of firms over time in our sample. The rapid increase in the first half of the sample is mostly a result of the growth of the CDS market in recent years. It then turns flat during the second half of the sample because of our requirement on the length of data coverage. To our knowledge, the Markit CDS data are not backfilled. The coverage for an obligor starts once a sufficient number of dealers start quoting its CDS contracts. It is possible for an obligor to exit the database for a number reasons, such as the pre-specified credit events, merger and acquisition, and so on. We do not anticipate the survivorship bias induced by our data coverage requirement to be an issue for the purpose of our study. Figure 2 also shows the number of investment-grade and speculative-grade obligors in our sample. Approximately 17 percent of the obligors are rated below investment-grade.

Table 1 presents the cross-sectional summary statistics of the time-series mean of the variables used in our analysis. The average firm in our sample is quite large, with a market capitalization in excess of $20 billion. In comparison, the average size of S&P 500 companies is $22.5 billion in 2005. The average firm has performed remarkably well, 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. As Figure 2 shows, this is purely the result of more firms joining the sample during the second half of the sample period, in which the overall market has rallied from its earlier decline.

Table 1 also shows a number of other variables of interest. For example, the average 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 is much higher than the median CDS spread. Among the volatility measures, 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. The average firm-level implied volatility is 38.80 percent, less than the average firm-level 252-day historical volatility of 40.43 percent. However, this comparison is slightly misleading. Because the average maturity of options used in the calculation of our implied volatility measure is approximately four months, the right comparison should be against the realized volatility over the subsequent four-month period. The average of the latter measure is only 35.51 percent.

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

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. These tests are designed to delineate the incremental contribution of historical and implied volatilities toward explaining the time-variation of CDS spreads. Table 3 reports the cross-sectional averages of coefficient estimates and their t-statistics.

In each panel, 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, the evidence suggests that the implied volatility measure enjoys an edge over historical volatility in explaining CDS spreads. 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).

To further evaluate the impact of historical and implied volatilities on CDS spreads, we expand the set of regressors to include additional variables as described in Section 2, and estimate the following regression:

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

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. Table 4 shows that the average coefficient on the firm implied volatility skew is positive, although generally not 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.

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 (see Duffee (1998)). The coefficient for the Baa yield is positive and significant, which can be attributed to the close relationship between bond and CDS markets (see Longstaff, Mithal, and Neis (2005) and Blanco, Brennan, and Marsh (2005)). 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 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 is insignificant with an average t-statistics of 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 five 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.[12]

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 historical volatility in its informativeness for CDS spreads.

3.2 Sub-Sample Results

To better understand the relation between CDS spreads and implied volatility, we partition our sample firms according to several firm-level characteristics and summarize the regression results for each sub-sample.

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

A related question is whether the information content of implied volatility for CDS spreads would vary across firms with different credit ratings. Among the sample firms,

[12] 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 significantly larger than the average β_1.

we observe a broad spectrum of credit quality, ranging from AAA (investment-grade) to CCC (speculative-grade).[13] We note that information asymmetry is expected to be larger for lower-rated firms. Banks and other informed traders/insiders are likely to explore their information advantage in both the CDS and options markets among these firms, not higher-rated firms with lower credit risk. We therefore sort the cross-section of firms according to their credit ratings.

Lastly, we sort the firms into three equal groups by their average option volume and open interest. While it has been argued that informed investors prefer to trade options because of their inherent leverage, the success of their strategy depends on a sufficiently liquid market. To the extent that market illiquidity or trading cost constitutes a “barrier to entry,” we expect the “signal-to-noise” ratio of implied volatility to be higher for firms with better option 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. We also use the ratio of the option open interest to the total common shares outstanding. 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.

Table 5 contains a summary of individual firm regression results for each sub-group of firms. For simplicity, only the average coefficients and t-statistics associated with the historical and implied volatilities are given. Panel A presents results on the three CDS volatility sub-groups. 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 (Group 3). The average t-statistics also increases monotonically, to 3.85 for Group 2 and 6.23 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. These results confirm a more important role of implied volatility for firms with more volatile CDS spreads. Note that even among the least volatile group, the implied volatility appears to be more informative than the historical volatility.

[13]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 the sample period and not the average rating, as only the former is available in our CDS dataset.

In Panel B we partition the sample firms by option volume. The results demonstrate that implied volatility becomes a more significant regressor as the option-to-stock volume ratio increases. For Group 1, which comprises of firms with the lowest option-to-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-to-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-to-stock volume ratio groups appears to be monotonic. In contrast, the size of the historical volatility coefficient is the smallest among the group with the largest option-to-stock volume ratio, where the average t-statistic is merely 1.17 for historical volatility, but 5.99 for implied volatility. The results in Panel C on option open interest are similar.

In Panel D we partition the sample firms by credit rating. 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 sub-groups: AA and above, A, BBB, and BB and below. The majority of our sample firms are rated BBB. 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 is reduced. The average coefficients for implied volatility among the four sub-groups 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 collective evidence presented in Table 5, we conclude that options market information is particularly useful in explaining CDS spreads for firms with low credit ratings, highly volatile CDS spreads, and high options market liquidity.

4 Lead-Lag Relation Among Stock, Option, and CDS Markets

The analysis in the preceding section has focused on the contemporaneous relation between CDS spread and implied volatility. An analysis of the lead-lag relation among stock, option, and CDS markets, however, could yield additional insight into the process of price discovery in these markets. Following Acharya and Johnson (2005), we first estimate a residual component of the changes in CDS spread and implied volatility, and the stock return that contains information unique to each market. This is accomplished by projecting each variable onto the space spanned by its own lagged values, as well as the contemporaneous and lagged values of the other two variables. For example, to estimate the CDS market residual $r_{CDS,t}$, we estimate the following regression equation using daily data for each firm:

$$\Delta CDS_t = \alpha + \sum_{i=1}^{3} \beta_i \Delta CDS_{t-i} + \sum_{i=0}^{3} \gamma_i \Delta IV_{t-i} + \sum_{i=0}^{3} \delta_i R_{S,t-i} + r_{CDS,t}, \tag{4}$$

where ΔCDS and ΔIV are changes in the CDS spread (in basis points) and implied volatility (in percentages), respectively, and R_S is the stock return (in percentages). The estimation of the stock market residual $r_{S,t}$ and the options market residual $r_{IV,t}$ follows in a similar manner.[14]

We then examine how each market residual affects the subsequent changes in other markets by estimating the following regression equations:

$$R_{S,t} = \alpha_S + \beta_{S,CDS} r_{CDS,t-1} + \beta_{S,IV} r_{IV,t-1} + \beta_{S,S} r_{S,t-1} + \varepsilon_{S,t}, \tag{5}$$

$$\Delta CDS_t = \alpha_{CDS} + \beta_{CDS,CDS} r_{CDS,t-1} + \beta_{CDS,IV} r_{IV,t-1} + \beta_{CDS,S} r_{S,t-1} + \varepsilon_{CDS,t}, \tag{6}$$

$$\Delta IV_t = \alpha_{IV} + \beta_{IV,CDS} r_{CDS,t-1} + \beta_{IV,IV} r_{IV,t-1} + \beta_{IV,S} r_{S,t-1} + \varepsilon_{IV,t}. \tag{7}$$

Because the predictability of CDS spread and implied volatility changes and stock returns at the firm-level is small, we follow Acharya and Johnson (2005) to estimate each of the above equations by panel regression.

Table 6 presents the results of our analysis. Specifically, we focus our discussion on $\beta_{S,CDS}$ and $\beta_{S,IV}$, which measure the incremental information revelation in the CDS and options markets relative to the stock market, and $\beta_{CDS,IV}$ and $\beta_{IV,CDS}$, which gauge the incremental information revelation across the CDS and option markets. In Panel A, we estimate equations (5)-(7) for each of the three CDS spread volatility groups. We find that changes in both the CDS spread and the implied volatility can forecast future stock returns. Both $\beta_{S,CDS}$ and $\beta_{S,IV}$ are decreasing with the CDS spread volatility. While $\beta_{S,IV}$ is negative and significant across all three groups, $\beta_{S,CDS}$ is negative and significant for only the most volatile group of firms. These results complement Acharya and Johnson (2005)'s finding that CDS spread changes can forecast future stock returns among firms experiencing a dramatic change in credit conditions. Specifically, not only CDS spreads but also put-option-implied volatilities contain important information for future stock returns. Intuitively, informed traders with negative information on the firm can purchase CDS contracts written on the firm's debt, bidding up the CDS spread. Alternatively, they can buy

[14] Using the AIC criterion, we find that the above specificaiton with three lags is sufficient.

put options on the firm's stock, bidding up the prices on these options and increasing the associated implied volatility. Our results on $\beta_{S,CDS}$ and $\beta_{S,IV}$ are entirely consistent with this intuition. As for the interpretation of these coefficients, among the most volatile group, a 100bp increase in the CDS spread residual causes a -0.85 percent stock return over the next day. Similarly, a one percent increase in the implied volatility residual causes a -0.31 percent stock return over the next day. These are economically meaningful effects on the stock return.

The results on the relation between the CDS and option markets are also interesting. For example, based on the estimates of $\beta_{CDS,IV}$, a one percent increase in the implied volatility residual triggers a positive and significant change in the CDS spread over the next day. This effect is increasing in the CDS spread volatility, starting at 0.16bp for the least volatile group and ending at 1.15bp for the most volatile group. On the other hand, the estimates of $\beta_{IV,CDS}$ show that a 100 bp increase in the CDS spread residual causes the implied volatility over the next day to increase 0.44 percent among the least volatile group. While this effect is significant, it declines with the CDS spread volatility and becomes negative and insignificant (-0.08 percent) among the most volatile group of firms. These results support the notion that the individual stock options market plays a special role in the price discovery process even in the presence of a competing market on credit derivatives.

To reaffirm the above results, we also estimate equations (5)-(7) for firms in the four credit rating groups. Panel B of Table 6 shows that both CDS and option market information can forecast future stock returns. This result becomes stronger as the credit quality of the firm declines in the cross-section. For firms rated BB or below, a 100 bp (one percent) increase in the CDS spread (implied volatility) residual causes a -1.0 (-0.35) percent stock return over the next day. Moreover, innovations in the options market can consistently forecast changes in the CDS spread, but not the other way around. These results are qualitatively the same as those for the CDS spread volatility groups in Panel A.

5 The Role of the 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 environment. 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. 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 volatility. However, their sample is limited to a small cross-section of 10 stocks. In any case, whether implied volatility can predict future realized volatility on individual stocks is itself an interesting and unanswered question.

More importantly, it is generally held that the difference between implied volatility and the expected future volatility is due to a volatility risk premium. For example, Chernov (2002) shows that in a fairly general model of stochastic volatility, the difference between the Black-Scholes implied volatility and the expected future volatility under the objective measure can be expressed as a function of the risk premia of the stochastic volatility. Therefore, 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 nature of the CDS-IV relation along these lines.

First, we perform time-series regressions of future realized volatility (FV) on either implied (IV) or historical volatility (HV) or both for each firm, and report the cross-sectional average of coefficients and t-statistics. The estimated regression model for each firm is:

$$FV_t = \alpha + \beta_1 HV_t + \beta_2 IV_t + \varepsilon_t. \tag{8}$$

Because the average maturity for the options used in our implied volatility estimation is about four months, both HV and FV are computed over 84 trading days in this exercise in order to match the horizon of option-implied volatility. We use daily data for the regression with the Newey and West (1987) correction to the standard errors for autocorrelation and heteroscedasticity.[15]

Our results can be found in Table 7. 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 86 percent of the obligors, as opposed to only 26 percent for historical volatility (β_1). Similarly, in 68 percent of the cases we can reject the hypothesis of $\beta_1 = \beta_2$

[15] Canina and Figlewski (1993) and Jorion (1995) use a similar correction to address the problem with volatilities measured on overlapping periods. Because our regressions utilize daily data on options with an average maturity of four months, we estimate Newey and West standard errors up to 126 lags. The estimated standard errors remain similar to those presented here.

in favor of $\beta_2 > \beta_1$, but in only 11 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 (0.68). The intercept is on average positive (10.84). 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. Following the literature such as Bakshi and Kapadia (2003), we compute the difference between implied volatility and future realized volatility, $IV - FV$, as our proxy of the volatility risk premium. The cross-sectional average of the time-series mean IV and 84-day future realized volatility are 38.80 percent and 35.51 percent, respectively, indicating a negative volatility risk premium.[16]

Strictly speaking, the volatility risk premium should be defined as $IV - E(FV)$. However, this introduces a separate problem of having to identify a good estimate of expected future volatility. Our solution is to simply regress the CDS spread on future volatility and the difference between implied and future volatility, 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, its effect on CDS spreads is unlikely to be subsumed by a volatility forecast, no matter how accurate the forecast is. Admittedly, the use of FV and $IV - FV$ instead of $E(FV)$ and $IV - E(FV)$ causes the estimated coefficients to be subject to an error-in-variables problem.[17] Because the size of this bias depends on the measurement error of $E(FV)$, we also use alternative proxies for $E(FV)$, such as the historical volatility HV or the projection of FV onto the space spanned by IV and HV, which is the fitted value of FV in the predictive regression of Table 7. These results are similar to those presented below, and are therefore omitted.

Another issue with the interpretation of $IV - FV$ as a volatility risk premium has to do with the fact that default risk may impact option prices directly. This element of default risk is independent of the usual notion of asymmetric volatility, and can be important for individual equity options (see Linetsky (2006)). Nevertheless, the regression analysis below incorporates standard controls for firm-level default risk, such as realized/historical

[16] The typical "volatility arbitrage" sells option straddles and profits from the difference between implied and realized volatility that is positive on average. In other words, selling delta-neutral option positions will generate positive average excess returns. This is what we mean by the volatility risk premium being "negative."

[17] Because of the perfectly negatively correlated measurement errors, the usual conclusion of a downward biased estimate does not apply here. See Appendix A for more details.

volatility, leverage, and firm stock returns. Consequently, we continue to treat $IV - FV$ as a volatility risk premium.

Panel A of Table 8 shows the results of regressing CDS spreads on FV and $IV - FV$. Compared to the benchmark regression results in Table 4, we see that the coefficient on FV is much larger than the coefficient on HV. It is also highly significant, which is suggestive of a tight relation between CDS spread and volatility, given the right volatility estimator. Most notably in Table 8, however, is that $IV-FV$ remains highly significant in the presence of FV. These results are qualitatively the same when we define a rescaled version of the volatility risk premium as $(IV - FV)/FV$ (see Panel B). Therefore, to model the CDS spread properly, it is useful to 1) have a good description of the behavior of volatility under the objective measure, and 2) incorporate a time-varying volatility risk premium. Our evidence suggests that each of these holds its own when it comes to explaining CDS spreads.

6 Robustness Results

6.1 Pricing Analysis

To more effectively address the nonlinear dependence of the CDS spread on its determinants, 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. Specifically, we use the CreditGrades model, an industry benchmark jointly developed by RiskMetrics, JP Morgan, Goldman Sachs, and Deutsche Bank. A detailed documentation of this model is given in Appendix B. Although a full menu of structural models have been developed following the seminal work of Merton (1974), we choose this industry model for three reasons. First, it appears to be widely used by practitioners (see Currie and Morris (2002)). Second, it contains an element of uncertain recovery rates, which helps to generate realistic short-term credit spreads. Third, the model yields a simple analytic CDS pricing formula. We are aware of the general concern of model misspecification when choosing to work with any particular model. Our methodology, however, is applicable to other structural models in a straightforward manner, which we leave to future research.

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

$$CDS_t = f\left(S_t, D_t, r_t, \sigma_t, T-t; \overline{L}, \lambda, R\right), \tag{9}$$

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

$$SSE = \min_{\overline{L},\lambda,R} \sum_{i=1}^{N} \left(\frac{\widehat{CDS}_i - CDS_i}{CDS_i} \right)^2. \tag{10}$$

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

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 percentage RMSE divided by the historical volatility-based percentage RMSE. This ratio varies substantially in the cross-section, with a median value of 0.95. 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, credit rating, leverage ratio, and total assets.

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-to-stock volume ratio appears to be insignificant. To put these coefficients (in Regression Three) into perspective, consider the median value of Ratio_RMSE at 0.95. A one-standard-deviation increase in the CDS spread volatility would lower it to

0.88. A one-standard-deviation increase in the option open interest would lower it further to 0.80. Lower the credit rating by one standard deviation reduces Ratio_RMSE still to 0.70. It appears that for firms with higher CDS spread 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 relative to when historical volatility is used in the same calibration. This result is broadly consistent with our regression findings in Section 3.

6.2 Historical Volatilities with Alternative Horizons

So far, we have compared the information content of implied volatility to that of the 252-day historical volatility in predicting CDS spreads. In this section we present evidence on historical volatilities with other estimation horizons. 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.

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.

We then repeat the pricing exercise of Section 6.1 with different historical volatility estimators. When we conduct the cross-sectional pricing error analysis following Table 9, we find similar results. 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 explanatory power of the different historical volatility estimators varies in the regression analysis, implied volatility continues to be more informative among the same subset of firms identified in 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 out on important credit events that are reflected in CDS spreads. On the other hand, short-horizon historical volatilities may be more attuned to market-moving news, but they are far too noisy to yield any improvement over the information content of implied volatility.[18] We therefore conclude that the information advantage of implied volatility is robust to historical volatility estimators of different horizons.

7 Conclusion

Can we use options market information to explain the pricing of credit default swaps, a newly developed and rapidly growing segment of the derivatives market? How does the information content of option-implied volatility for CDS spreads vary among the cross-section of firms? What is the role of the volatility risk premium in the CDS-IV relation? These are some of the questions that we address in this paper. Our motivation mainly derives from the growing academic literature highlighting the information content of equity options and credit default swaps for predicting returns on the underlying stocks (see Cao, Chen, and Griffin (2005), Pan and Poteshman (2006), and Acharya and Johnson (2005)). The natural extension of this idea is that options market information, such as implied volatility, can be useful for explaining CDS spreads. We are also partially motivated by the 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 using the CreditGrades model, the ratio between the RMSE with implied volatility and the 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

[18] It is unlikely that short-horizon realized volatility would dominate in this context. For example, Zhang, Zhou, and Zhu (2005) regress CDS spreads on both the one-year historical volatility and the one-month realized volatility estimated from intradaily returns. Both apppear to be significant in explaining CDS spreads.

alternative estimation horizons.

Besides analyzing the contemporaneous relation between CDS spreads and implied volatility, we also conduct a lead-lag analysis of changes in the stock, option, and CDS markets. We find that both CDS and option market information can be used to forecast future stock returns. This forecasting power increases with the volatility of the CDS spread and decreases with credit quality in the cross-section of firms. Interestingly, although changes in implied volatility can consistently forecast changes in the CDS spread, the reverse does not hold among the most volatile and lowest-rated firms. Our results suggest that the options market plays a special role in the price discovery process among the three markets.

To further shed light on the nature of the CDS-IV relation, we conduct predictive regressions of future volatility on the implied and historical volatility of individual stocks. We find implied volatility to be an informative but biased forecast of future stock return volatility. For the majority of the obligors, implied volatility dominates historical volatility in predicting future volatility. We also regress CDS spreads on proxies of expected future volatility as well as the volatility risk premium. We find both variables to figure prominently in the determination of CDS spreads. Therefore, implied volatility explains CDS spreads not only because it forecasts future volatility, but also because it captures a time-varying volatility risk premium.

Appendix

A Estimation Bias of Regressing CDS Spread on FV and $IV - FV$

Assume that the CDS spread is linearly related to the expected future volatility and the volatility risk premium as follows:

$$y = \beta_1 x_1^* + \beta_2 x_2^* + \epsilon, \tag{11}$$

where y is the CDS spread, $x_1^* = E(FV)$, $x_2^* = IV - E(FV)$, and ϵ is uncorrelated with x_1^* and x_2^*.

In the tradition of error-in-variables problems, let

$$x_1 = x_1^* + u,\ x_2 = x_2^* - u, \tag{12}$$

where u is a measurement error uncorrelated with x_1^*, x_2^*, and ϵ. In our context u would be defined as $FV - E(FV)$.

Let n represent the number of observations that will approach infinity. We have the following result on the OLS estimator b:

$$\begin{aligned}
\text{plim } b &= \text{plim } \left[\frac{1}{n}\begin{pmatrix} x_1'x_1 & x_1'x_2 \\ x_2'x_1 & x_2'x_2 \end{pmatrix}\right]^{-1} \text{plim } \frac{1}{n}\begin{pmatrix} x_1'y \\ x_2'y \end{pmatrix} \\
&= \begin{pmatrix} Q_1 + \sigma_u^2 & \rho\sqrt{Q_1Q_2} - \sigma_u^2 \\ \rho\sqrt{Q_1Q_2} - \sigma_u^2 & Q_2 + \sigma_u^2 \end{pmatrix}^{-1} \begin{pmatrix} \beta_1 Q_1 + \beta_2\rho\sqrt{Q_1Q_2} \\ \beta_2 Q_2 + \beta_1\rho\sqrt{Q_1Q_2} \end{pmatrix},
\end{aligned} \tag{13}$$

where $Q_1 = \text{plim } \frac{1}{n}x_1^{*\prime}x_1^*$, $Q_2 = \text{plim } \frac{1}{n}x_2^{*\prime}x_2^*$, $\rho\sqrt{Q_1Q_2} = \text{plim } \frac{1}{n}x_1^{*\prime}x_2^*$, and $\sigma_u^2 = var(u)$. Further simplifying the above expression, we obtain:

$$b_1 = \beta_1 + \frac{\left(Q_2 + \rho\sqrt{Q_1Q_2}\right)\sigma_u^2}{(1-\rho^2)\,Q_1Q_2 + \left(Q_1 + Q_2 + 2\rho\sqrt{Q_1Q_2}\right)\sigma_u^2}\,(\beta_2 - \beta_1)\,, \tag{14}$$

$$b_2 = \beta_2 + \frac{\left(Q_1 + \rho\sqrt{Q_1Q_2}\right)\sigma_u^2}{(1-\rho^2)\,Q_1Q_2 + \left(Q_1 + Q_2 + 2\rho\sqrt{Q_1Q_2}\right)\sigma_u^2}\,(\beta_1 - \beta_2)\,. \tag{15}$$

Unlike the standard error-in-variables problem, the OLS estimator is not necessarily downward biased. For example, if ρ is positive and the true coefficients satisfy $\beta_1 > \beta_2$, then b_2 will be upward biased. Intuitively, the size of the biases depends on the ratio of σ_u^2 to Q_1 and Q_2.

B The CreditGrades Model

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

$$\frac{dV_t}{V_t} = \sigma dW_t, \tag{16}$$

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

$$L = \overline{L} e^{\lambda Z - \lambda^2/2}, \tag{17}$$

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:[19]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{18}$$

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

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

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

$$c = -\frac{(1-R)\int_0^T e^{-rs} dq(s)}{\int_0^T e^{-rs} q(s)\, ds}. \tag{19}$$

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

$$c(0,T) = r(1-R)\frac{1 - q(0) + H(T)}{q(0) - q(T)e^{-rT} - H(T)}, \tag{20}$$

[19] 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.

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

$$\sigma = \sigma_S \frac{S}{S + \overline{L}D}, \tag{21}$$

which completes the specification of the CreditGrades model.

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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, Option Volume, Open Interest, and Credit Rating

Cross-sectional averages of coefficients and t statistics (in parentheses) of time-series regressions partitioned by CDS spread volatility, option volume, open interest, and 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. For simplicity, only the historical and implied volatility coefficients are reported.

Panel A: By CDS Spread Volatility

	Group1 (Least volatile)	Group2	Group3 (Most volatile)
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)
Firm- and Market-Level Control Variables	-	-	-
Number of Firms	73	74	73

Panel B: By Option Volume

	Group1 (Smallest)	Group2	Group3 (Largest)
Historical Volatility (β1)	1.02	1.14	0.75
	(1.40)	(1.21)	(1.17)
Implied Volatility (β2)	2.33	2.60	4.29
	(3.37)	(3.90)	(5.99)
Firm- and Market-Level Control Variables	-	-	-
Number of Firms	73	74	73

Panel C: By Option Open Interest

	Group1 (Smallest)	Group2	Group3 (Largest)
Historical Volatility (β1)	0.68	0.61	1.63
	(1.21)	(1.01)	(1.56)
Implied Volatility (β2)	2.35	2.34	4.53
	(3.46)	(3.94)	(5.85)
Firm- and Market-Level Control Variables	-	-	-
Number of Firms	73	74	73

Panel D: By Credit Rating

	AA and above	A	BBB	BB and below
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)
Firm- and Market-Level Control Variables	-	-	-	-
Number of Firms	13	60	109	38

Table 6. Lead-Lag Analysis of Changes of the CDS Spread and Implied Volatility, and the Stock Return

Coefficients and t statistics (in parentheses) of pooled OLS regressions of changes of the CDS spread and implied volatility, and the stock return for each of the CDS spread volatility and the credit rating sub-groups. The regression equations and the coefficients are defined in equations (5)-(7). The sample period extends from January 2001 through June 2004.

Panel A: By CDS Spread Volatility

	Group1 (Least volatile)	Group2	Group3 (Most volatile)
$\beta_{S,CDS}$	0.0026	-0.0009	-0.0085
	(0.66)	(-0.42)	(-11.28)
$\beta_{S,IV}$	-0.050	-0.077	-0.31
	(-3.27)	(-5.56)	(-32.89)
$\beta_{CDS,IV}$	0.16	0.22	1.15
	(7.75)	(6.70)	(17.65)
$\beta_{IV,CDS}$	0.0044	0.0024	-0.0008
	(2.65)	(2.60)	(-1.76)
Number of Firms	73	74	73

Panel B: By Credit Rating

	AA and above	A	BBB	BB and below
$\beta_{S,CDS}$	0.0060	0.0068	-0.0010	-0.010
	(0.69)	(2.25)	(-0.98)	(-10.52)
$\beta_{S,IV}$	-0.12	-0.035	-0.078	-0.35
	(-3.27)	(-2.01)	(-7.39)	(-29.39)
$\beta_{CDS,IV}$	0.0013	0.28	0.86	1.02
	(0.02)	(8.66)	(19.04)	(11.80)
$\beta_{IV,CDS}$	-0.0029	0.0026	0.0011	-0.00092
	(-0.69)	(2.07)	(2.11)	(-1.53)
Number of Firms	13	60	109	38

Table 7. 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 84-day future realized volatility. The independent variables are the 84-day historical volatility and/or the implied volatility. 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	21.28	8.80	10.84
	(8.70)	(3.03)	(2.85)
Historical Volatility (β_1) – 84 trading days	0.38		-0.06
	(7.21)		(-0.33)
Implied Volatility (β_2)		0.66	0.68
		(9.39)	(6.10)
Adjusted R^2	20%	28%	34%
Percentage of t's ≥ 1.96 (β_1, Historical Volatility)	89%		26%
Percentage of t's ≥ 1.96 (β_2, Implied Volatility)		97%	86%
Percentage of t's ≥ 1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2>\beta_1$)			68%
Percentage of t's ≤ -1.64 (H_0: $\beta_2=\beta_1$ vs. H_1: $\beta_2<\beta_1$)			11%

Table 8. Time-Series Regression Analysis of CDS Spreads Using Future Realized Volatility and the Volatility Risk Premium

Cross-sectional averages of coefficients and t statistics (in parentheses) 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 independent variables include the 84-day future realized volatility, the difference between the implied volatility and the 84-day future realized volatility, and other variables defined 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. For simplicity, only the two main coefficients are reported. Regressions 1 to 4 are similarly defined as in Table 4.

Panel A: "Standard" Volatility Risk Premium

	1 No control	2 Firm-level control	3 Market-level control	4 All controls
Intercept	-102.25	-188.56	-185.41	-224.10
	(-6.29)	(-3.18)	(-2.84)	(-2.87)
FV84 (β_1)	5.76	4.22	4.21	3.00
	(16.65)	(10.41)	(7.29)	(3.85)
(IV – FV84) (β_2)	5.09	3.64	3.65	2.99
	(11.86)	(8.02)	(6.47)	(4.42)
Firm- and Market-Level Control Variables	-	-	-	-

Panel B: "Rescaled" Volatility Risk Premium

	1 No control	2 Firm-level control	3 Market-level control	4 All controls
Intercept	-102.43	-250.55	-252.81	-357.84
	(-5.65)	(-3.73)	(-3.34)	(-3.63)
FV84 (β_1)	5.58	3.41	2.84	1.49
	(14.37)	(8.36)	(5.41)	(1.97)
(IV – FV84) / FV84 (β_2)	1.95	1.06	0.87	0.65
	(10.15)	(6.29)	(4.49)	(2.64)
Firm- and Market-Level Control Variables	-	-	-	-

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.

	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 horizons. 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%

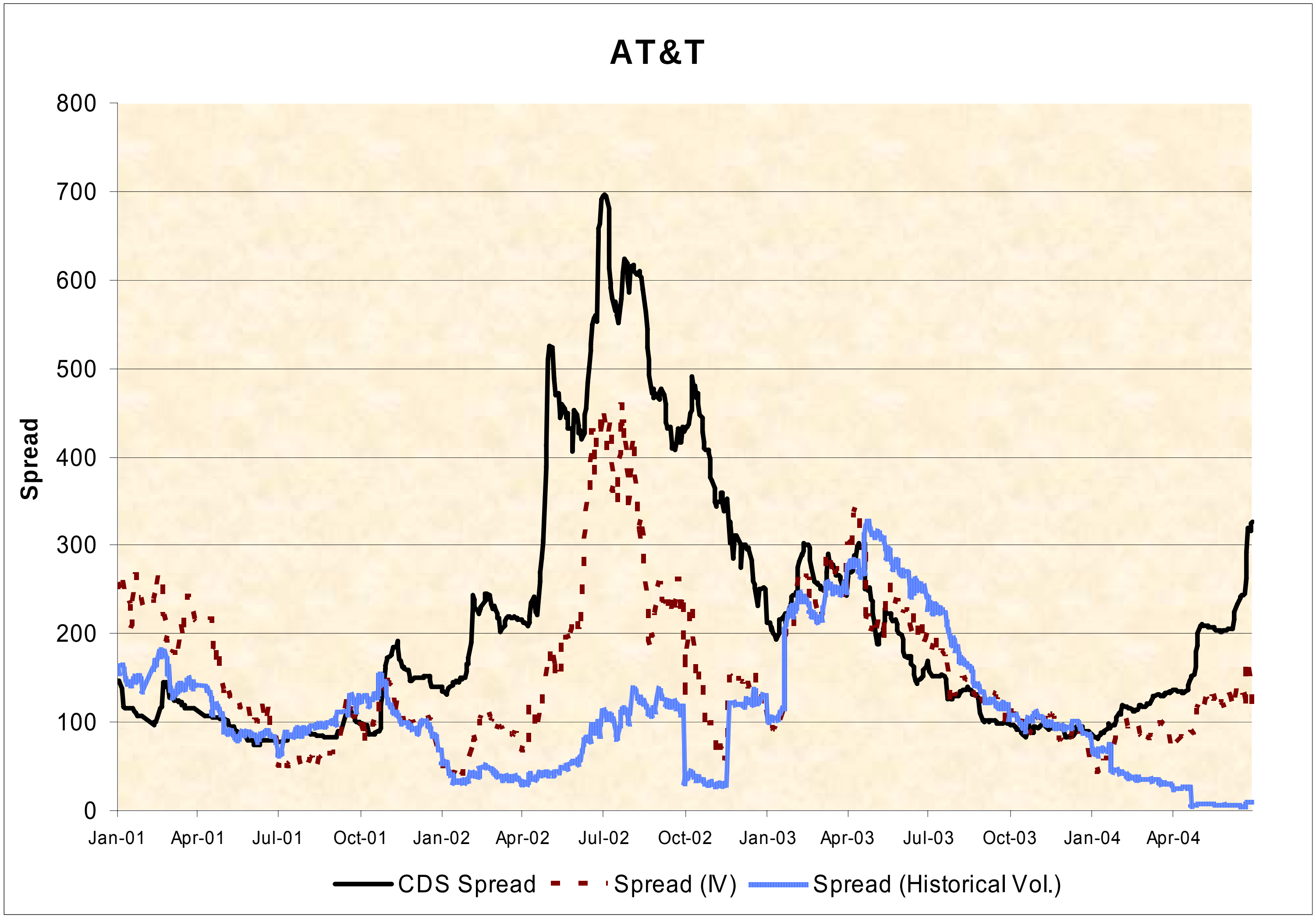

Figure 1. AT&T CDS Spreads

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.

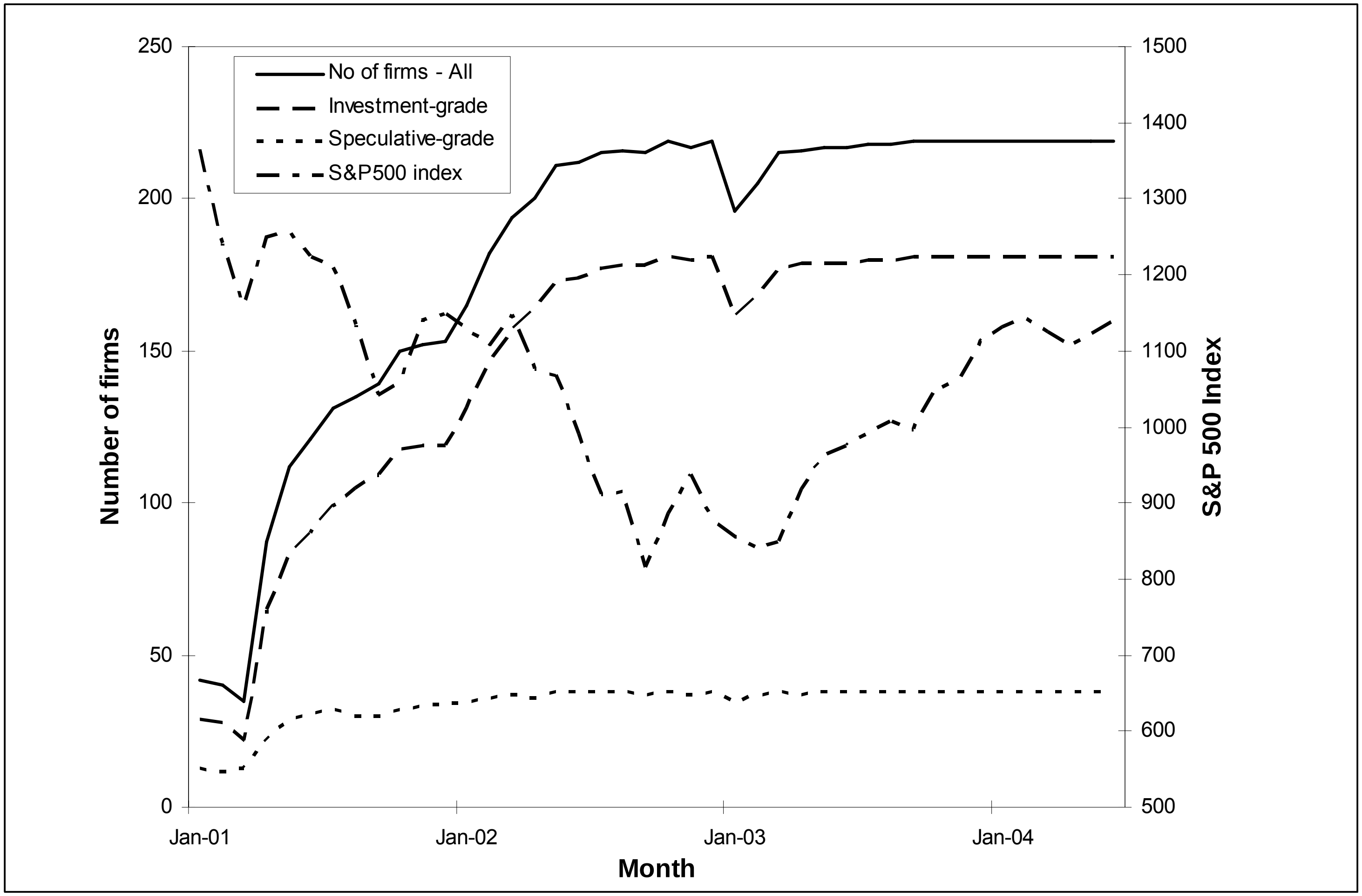

Figure 2. The Number of Firms Each Month

Number of firms for each month is the total number of firms included in our sample at the beginning of each month. Firms with credit rating at or above Standard and Poor's BBB rating are considered investment-grade. Those rated below this level are considered speculative-grade. The S&P 500 Index is the level of the S&P 500 Composite Index.