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The information content of option-implied volatility for credit default swap valuation

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Abstract

Credit default swaps (CDS) are similar to out-of-the-money put options in that both offer a low cost and effective protection against downside risk. This study investigates whether put option-implied volatility is an important determinant of CDS spreads. Using a large sample of firms with both CDS and options data, we find that individual firms' put option-implied volatility dominates historical volatility in explaining the time-series variation in CDS spreads. To understand this result, we show that implied volatility is a more efficient forecast for future realized volatility than historical volatility. More importantly, the volatility risk premium embedded in option prices covaries with the CDS spread. These findings complement existing empirical evidence based on market-level data.

JEL classification: G11; G12; G14

Keywords: Credit default swaps; Option implied volatility; Historical volatility; Price discovery; Volatility risk premium

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

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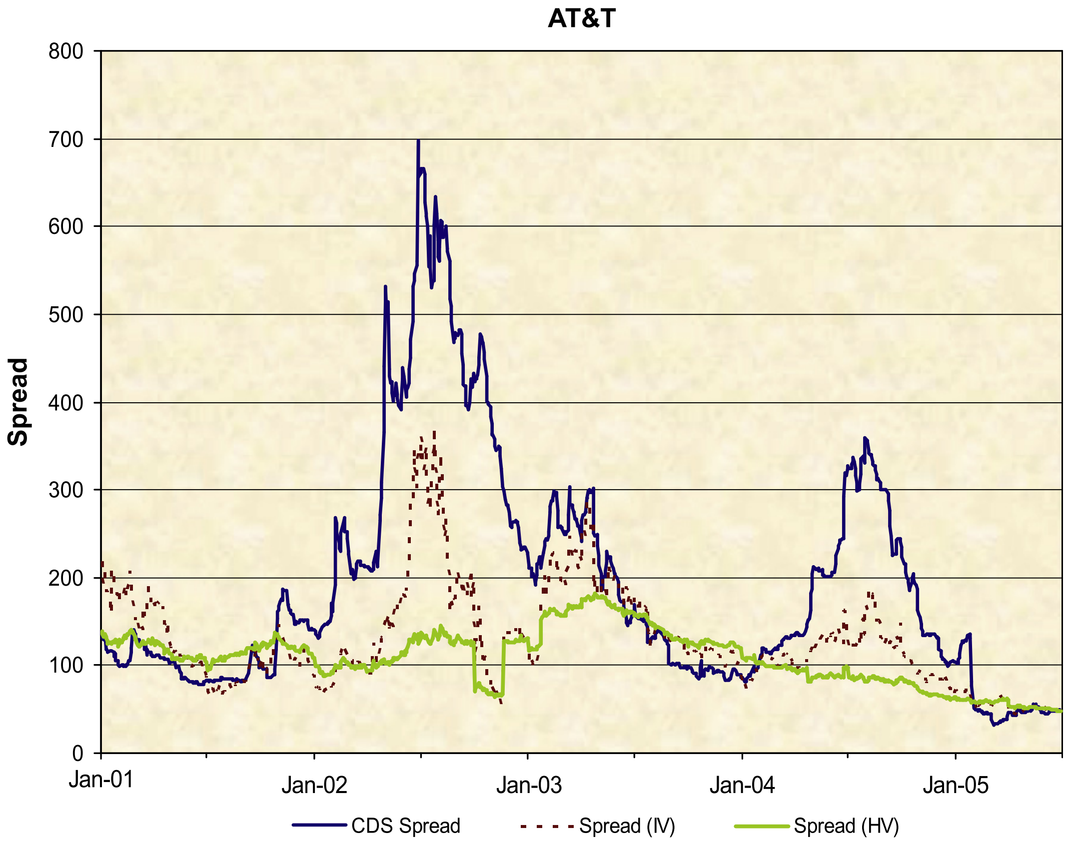

Fig. 1. AT&T CDS spreads. This figure plots the time-series of CDS spreads of AT&T Corp. from January 2001 to June 2005 before it was acquired by SBC. CDS Spread is the market CDS spread provided by Markit Group. Model Spread (*IV*) is the spread computed by a structural model (CreditGrades) using the option-implied volatility as input. Model Spread (*HV*) is the spread computed by the CreditGrades model using the 252-day historical volatility as input.

premium (as a percentage of the notional value of the bonds or loans each quarter and denoted as an annualized spread in basis points) and receives the payoff from the seller, should a credit event occur prior to the expiration of the contract. Fueled by the eagerness of 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 \$62 trillion in notional amount outstanding by the end of 2007.[1]

This dramatic development obviates the need for a better understanding of the valuation of credit risk. In response, a recent strand of literature has recognized the important role of firm-level volatility in the determination of CDS spreads (e.g., Collin-Dufresne et al., 2001; Ericsson et al., 2009; Zhang et al., 2009). Considering that 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 protection against downside risk, we conduct a comprehensive analysis of the relation between CDS spreads and option-implied volatilities.[2] The rationale for relying

[1]See the International Swaps and Derivatives Association 2007 year-end market survey.

[2]There is, however, one important difference. Conditional on default, the CDS payoff is related to the recovery rate of the underlying obligation, while the put payoff is equal to the strike price (assuming a stock price of zero). To the extent that recovery risk is macroeconomic (Altman et al., 2003), the effect of recovery risk on CDS spreads is partially addressed by the list of macroeconomic variables included in our analysis.

on implied volatility as an important explanatory variable for the time-series behavior of CDS spreads is also evident from Fig. 1, where we fit an industry benchmark credit risk model called CreditGrades to AT&T CDS spreads, using either the 252-day historical volatility or the put 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 200 to 700 basis points.[3]

Using a broad sample of 301 firms with both CDS and options data, 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. We find that implied volatility dominates historical volatility in explaining the time-series variation of CDS spreads, and that this result is robust to the horizon of the historical volatility estimator. In further robustness analyses, we find that both the magnitude and statistical significance of implied volatility are more pronounced among firms with lower credit ratings, higher CDS spread volatilities, and more actively traded options. Moreover, changes in implied volatility are associated with future CDS spread changes among our sample firms. Overall, our findings are consistent with a special role of options market information in explaining the time-series variation of CDS spreads.

Probing deeper into the nature of the information content of option-implied volatility, we focus on the following question: Does implied volatility explain the time-series behavior of CDS spreads because it forecasts future volatility better, or because it captures a volatility risk premium? For the first part of this question, the extant literature has examined the power of implied volatility to predict future realized volatility, producing generally mixed evidence (Day and Lewis, 1992; Canina and Figlewski, 1993; Lamoureux and Lastrapes, 1993; Christensen and Prabhala, 1998; Jiang and Tian, 2005). As for the second part of the question, the difference between implied volatility and the expected future volatility under the objective measure is commonly regarded as a volatility risk premium (Bakshi and Kapadia, 2003; Bates, 2003; Chernov, 2007; Bollerslev et al., 2008, 2009; Zhou, 2009). Because of the similarity between the payoffs of out-of-the-money puts and credit default swaps, this risk premium component can, presumably, help to explain CDS spreads in a way that even the best volatility estimator cannot.

To address this important question, we first analyze the predictability of future realized volatility using historical and/or implied volatility. When included alone in the firm-level predictive regressions, historical (implied) volatility can explain 25% (33%) of the time-series variation of the CDS spread for the average firm in our sample. When both are included in the regressions, the average R^2 increases to 36%, and the effect of historical volatility is largely subsumed by that of implied volatility. On average, the intercept of the regression is positive, and the coefficient of implied volatility is less than unity. Therefore, we find implied volatility to be an informative, but biased, forecast of future realized volatility that tends to dominate historical volatility.

Measuring the expected future volatility as the output of the predictive regressions, we construct the volatility risk premium as the difference between implied volatility and the

[3]Indeed, 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."

predicted future volatility. We then regress the CDS spread on the predicted future volatility and the volatility risk premium. We find the volatility risk premium to be a significant determinant of CDS spreads even in the presence of the predicted future volatility. 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.

Our paper contributes to the extant literature in a number of ways. Campbell and Taksler (2003), Ericsson et al. (2009) and Zhang et al. (2009) have demonstrated a strong relation between credit spreads and equity historical volatilities. We focus instead on the relation between CDS spreads and options market information and show that option-implied volatility is an even more important determinant of CDS spreads than equity historical volatility. Cremers et al. (2008) estimate the relation between corporate bond yield spreads and options market variables. They adopt a panel regression approach, which relies on information from the cross-section of firms for identification. Motivated by the AT&T illustration (Fig. 1), we are more concerned about the time-series relation between the two markets for each individual firm; therefore, we estimate the relation between credit spreads and implied volatility using firm-level time-series regressions.

By combining firm-level CDS and options data, our paper advances the early literature on the information content of implied volatility. In particular, Lamoureux and Lastrapes (1993) use a sample of 10 firms to show that implied volatility is a biased forecast for future volatility, and they suggest that this bias can be attributed to a volatility risk premium. We extend their analysis to a sample of 301 firms. Our results show that the volatility risk premium is highly relevant when explaining the pricing of credit default swaps.

Our paper is also related to recent literature documenting the forecasting power of the volatility risk premium for market-level risk premiums and credit spreads. For example, Bollerslev et al. (2009) and Zhou (2009) develop a general equilibrium model that incorporates the effect of time-varying economic uncertainties. They construct the volatility risk premium from the model-free implied volatility and the high-frequency realized volatility, and show that it can forecast (1) returns on the S&P 500 index; (2) returns on Treasury bonds; and (3) Moody's Aaa and Baa corporate bond spreads. These empirical results are consistent with the implications of their model. Pan and Singleton (2008) extract the credit risk premium from sovereign CDS spreads and find that it covaries with the VIX index, which embeds the volatility risk premium. Our work extends this literature to the important single-name credit default swaps market and volatility risk premiums extracted from individual firms' stock options.

The rest of this paper is organized as follows. In Section 2, we summarize the data sources and variables used in our study. In Section 3, we conduct a regression-based analysis of the relation between the CDS and options markets. Section 4 examines the role of the volatility risk premium in explaining the CDS spread. Additional robustness results can be found in Section 5. We conclude with Section 6.

2. Data

2.1. Credit default swaps

As described in the Introduction, the CDS spread is the premium that is paid to insure the loss of value of 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 of the underlying obligation. Contrasting this with the yield spread of corporate bonds, which is affected by the choice of a risk-free benchmark yield along with the differential tax treatment and liquidity of corporate and Treasury bonds, the CDS spread is often perceived as a superior measure of default risk.

We collect single-name CDS spreads from a comprehensive database compiled by the Markit Group. The daily composite spreads are computed from quotes contributed by major market participants that undergo a statistical procedure by which outliers and stale quotes are removed. In addition, two or more contributors are needed before a daily composite spread is calculated, ensuring reasonable quality of 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 U.S. dollar-denominated five-year CDS contracts written on the senior unsecured debt of North American obligors. Although the maturity of the composite spread can range between six months and 30 years, five-year CDS contracts have become the most common in recent years. For example, Hull et al. (2004) estimate that more than 85% of all quotes in 2001 and 2002 are for five-year contracts. Similarly, the majority of the contracts are written on senior unsecured obligations.

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

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 for the CDS spread, the implied volatility, the 252-day historical volatility, and the leverage ratio. Furthermore, we eliminate firms with more than 20% missing observations between the first and last dates of their coverage. These requirements ensure that each obligor has at least one and a half years of uninterrupted daily data available for the firm-level time-series analysis. Combining all variables documented above, we arrive at a final sample of 301 firms during the period from January 2001 to December 2006.

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 2001 to 2006. This dataset also contains 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, 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 puts 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, many firms in our sample do not have actively traded, deep out-of-the-money puts. 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 puts that have non-zero open interest each day. The choice of non-zero open interest emphasizes the information content of options that are currently in use by market participants, and the choice of all puts 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 periodically switching from one contract to the next.

Besides the daily implied volatility measure, we also compute an implied volatility skew, which is the difference between the implied volatility of an out-of-the-money put option with a strike-to-spot ratio closest to 0.92, and the implied volatility of an at-the-money put option, further divided by the difference in the strike-to-spot ratios of the two option contracts used. Both 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.

2.3. *Other firm-level and market-level variables*

We obtain equity prices, common shares outstanding, and daily stock returns from CRSP, and we obtain 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.

We also include a list of market variables that can potentially explain the time-series variation of CDS spreads:

- *Market-level returns and volatilities*. The market implied volatility is taken as the 30-day at-the-money implied volatility of S&P 500 index put options. The market implied volatility skew is defined in the same way as the individual implied volatility skew, but it uses S&P 500 index puts. The market return is the annualized 252-day average S&P 500 index return. The market historical volatility is the annualized 252-day S&P 500 index volatility.
- *Default-free term structure level and slope*. For the yield curve level, we use the five-year Treasury yield. For the slope, we calculate the difference between the 10-year and the two-year Treasury yields. The Treasury yields are obtained from Datastream.
- *Market-level credit risk*. We use the Baa yield from Moody's.
- *Credit market illiquidity*. Feldhütter and Lando (2008) decompose the 10-year swap-Treasury spread into several components, one of which measures the convenience yield from holding Treasury securities. Because this component is likely to be large as

investors flee the credit market and seek refuge in the Treasury market, we take it as a measure of credit market illiquidity.[4]

2.4. Summary statistics

Table 1 presents the cross-sectional summary statistics of the time-series means of the variables used in our analysis. The average firm in our sample is quite large, with a market capitalization close to \$20 billion. In comparison, the average size of S&P 500 companies was \$22.5 billion. The average firm has performed remarkably well, with an annualized 252-day average stock return of 16.45%. In contrast, the annualized 252-day average return on the S&P 500 index is only 3.17%. This is an artifact of more firms joining the sample during the second half of the sample period, in which the overall market had rallied from its earlier trough. With respect to the composition of our sample in terms of credit rating, approximately 31% of the obligors are rated below investment-grade.

Table 1 shows a number of other interesting variables. For example, the average CDS spread is 143 basis points, although the cross-sectional standard deviation is 234 basis points, 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 17.61%, slightly higher than the mean market-level historical volatility of 16.91%. The mean market implied volatility skew of 0.77 is substantially larger than the mean firm-level implied volatility skew of 0.56.[5] The average firm-level implied volatility is 34.82%, higher than the average firm-level 252-day historical volatility of 33.28%.

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 the ratio of 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. We note that near-the-money options (those with moneyness between 0.8 and 1.2) are heavily traded. 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% of the total number of options. This is the subset of options from which we compute our daily implied volatility measure.

3. Regression analysis

We conduct time-series regressions for each of the 301 firms, in which the dependent variable is the daily CDS spread. In our benchmark regression, we include both the implied volatility (IV) and the 252-day historical volatility (HV), as well as additional control

[4]We are grateful to Peter Feldhütter and David Lando for sharing their Treasury convenience yield factor. Since our credit market illiquidity measure is constructed using a parametric model of the swap-Treasury spread (i.e., Feldhütter and Lando, 2008), in Section 5 we explore alternative measures of credit market illiquidity that are model-independent. These include the swap-Treasury spread itself, as well as the spread between on- and off-the-run 10-year Treasury yields.

[5]Bakshi et al. (2003) offer similar findings on the implied volatility skew for index and individual stock options.

Table 1
Summary statistics.

For each variable, Panel A reports the cross-sectional summary statistics of the time-series means of 301 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 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&P 500 index returns; market implied volatility is the 30-day ATM implied volatility of S&P 500 put options; market implied volatility skew is the implied volatility skew of S&P 500 put options; market return is the 252-day average of S&P 500 index returns; treasure rate is the five-year U.S. treasury constant maturity yield; yield curve slope is the difference between 10-year and two-year U.S. treasury yields; credit market illiquidity is the liquidity component of the swap spread; Baa rate is the average yield of U.S. corporate bonds rated Baa by Moody's. The sample period extends from January 2001 through December 2006.

	Mean	Q1	Median	Q3	Standard deviation
Panel A: Firm-level variables					
CDS spread (basis point)	142.81	39.05	67.15	180.15	234.02
Historical volatility (%)	33.28	26.07	30.93	38.16	11.19
Implied volatility (%)	34.82	28.38	33.00	39.06	9.84
Implied volatility skew	0.56	0.45	0.53	0.61	0.20
Leverage (%)	42.33	27.91	41.20	55.34	19.36
Firm stock return (%)	16.45	6.28	14.89	23.33	16.71
Market capitalization ($billion)	19.86	3.44	7.88	17.58	36.35
Panel B: Market-level variables					
Market historical volatility (%)	16.91	10.73	16.55	22.35	6.18
Market implied volatility (%)	17.61	11.89	15.98	21.11	6.88
Market implied volatility skew	0.77	0.65	0.75	0.88	0.18
Market return (%)	3.17	−12.47	7.67	13.87	16.11
Treasury rate (%)	3.93	3.28	3.96	4.57	0.74
Yield curve slope (%)	1.30	0.32	1.61	2.12	0.92
Credit market illiquidity (%)	0.54	0.44	0.50	0.66	0.13
Baa rate (%)	6.90	6.26	6.69	7.80	0.75

variables described in Section 2:

$$CDS_t = \alpha + \beta_1 HV_t + \beta_2 IV_t + \text{additional firm-specific variables} \\ + \text{market volatility variables} + \text{macro variables} + \varepsilon_t. \quad (1)$$

First, we find that the effect of these additional control variables on the CDS spread, if any, is consistent with theoretical predictions and the extant empirical evidence. Table 3 shows that the average coefficient of the firm-implied volatility skew is positive. This is in accordance with the implied volatility skew being a proxy for the risk-neutral skewness of the stock return distribution—the larger the skew, the higher the probability of default, and the higher the CDS spread. For the other firm-specific variables, the average coefficient of the firm leverage ratio is positive and highly significant, while the firm-level stock return appears insignificant.

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 for the 301 sample firms with options listed on all U.S. option markets. 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 December 2006.

Maturity	Moneyness				
	<0.8	0.8–1.0	1.0–1.2	>1.2	Subtotal
Panel A: All contracts					
<30 days	4,637 (4.61)	5,831 (6.71)	4,942 (5.73)	5,500 (5.57)	20,910 (22.61)
31–90 days	6,301 (6.22)	7,810 (8.97)	6,626 (7.66)	7,452 (7.49)	28,190 (30.34)
91–180 days	5,771 (5.71)	6,393 (7.27)	5,400 (6.18)	6,737 (6.77)	24,301 (25.93)
>180 days	5,075 (4.73)	5,315 (5.84)	4,505 (4.99)	5,861 (5.56)	20,756 (21.12)
Subtotal	21,784 (21.27)	25,348 (28.79)	21,474 (24.56)	25,550 (25.38)	94,156 (100.00)
Panel B: Contracts with volume					
<30 days	271 (0.76)	2,438 (10.03)	2,419 (10.55)	707 (2.23)	5,835 (23.57)
31–90 days	702 (2.06)	3,946 (16.57)	2,685 (11.09)	786 (2.40)	8,119 (32.12)
91–180 days	962 (2.86)	3,268 (14.04)	1,864 (7.53)	716 (2.16)	6,810 (26.59)
>180 days	984 (2.66)	2,317 (8.99)	1,223 (4.37)	633 (1.69)	5,157 (17.72)
Subtotal	2,919 (8.35)	11,969 (49.63)	8,191 (33.54)	2,842 (8.48)	25,921 (100.00)
Panel C: Contracts with open interest					
<30 days	3,003 (3.82)	5,212 (7.83)	4,291 (6.39)	3,300 (4.04)	15,806 (22.07)
31–90 days	4,323 (5.53)	6,662 (9.91)	5,210 (7.63)	4,358 (5.44)	20,554 (28.50)
91–180 days	4,915 (6.20)	6,200 (9.52)	4,898 (7.34)	4,772 (5.93)	20,785 (29.01)
>180 days	4,146 (4.77)	4,680 (6.58)	3,455 (4.69)	3,869 (4.38)	16,150 (20.42)
Subtotal	16,388 (20.32)	22,753 (33.84)	17,855 (26.05)	16,300 (19.79)	73,295 (100.00)
Panel D: Contracts with open interest–put only					
<30 days	1,692 (4.57)	2,595 (8.17)	2,070 (6.31)	1,243 (3.10)	7,600 (22.15)
31–90 days	2,412 (6.58)	3,229 (10.02)	2,523 (7.59)	1,687 (4.25)	9,851 (28.44)
91–180 days	2,649 (7.12)	2,998 (9.69)	2,419 (7.46)	1,966 (4.91)	10,032 (29.19)
>180 days	2,196 (5.40)	2,192 (6.39)	1,714 (4.74)	1,651 (3.70)	7,753 (20.23)
Subtotal	8,949(23.67)	11,014 (34.27)	8,726 (26.10)	6,547 (15.97)	35,236 (100.00)

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 (Duffee, 1998). The coefficient of the Baa yield is positive and significant, which can be attributed to the close relation between bond and CDS markets (Longstaff et al., 2005; Blanco et al., 2005). The coefficient of the credit market illiquidity factor is positive and significant, consistent with the ‘‘flight-to-quality'' interpretation of the Feldhütter and Lando (2008) Treasury convenience yield factor. Lastly, none of the market volatility variables is significant, which 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 55% in Regression 1 to 84% in Regression 4.

Table 3
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 301 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 (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006.

	1	2	3	4
Intercept	−82.73	−192.71	−177.84	−340.77
	(−6.09)	(−5.99)	(−5.15)	(−5.20)
Historical volatility (β_1)	1.08	0.92	0.60	0.69
	(3.53)	(2.58)	(1.89)	(1.82)
Implied volatility (β_2)	4.26	2.93	2.81	2.01
	(8.01)	(6.08)	(4.84)	(3.07)
Additional firm-specific variables				
Implied volatility skew		8.68	7.17	5.09
		(1.12)	(0.81)	(0.53)
Leverage		2.80	2.46	3.64
		(4.71)	(3.38)	(2.63)
Firm stock return		−0.02	−0.03	0.00
		(−0.12)	(−0.21)	(−0.12)
Market volatility variables				
Market historical volatility			1.53	1.09
			(0.59)	(0.03)
Market implied volatility			−0.05	−0.31
			(0.69)	(−0.47)
Market implied volatility skew			3.46	−2.10
			(0.98)	(0.26)
Macro variables				
Market return				0.05
				(1.21)
Treasury rate				−23.60
				(−3.24)
Yield curve slope				−14.58
				(−2.15)
Credit market illiquidity				93.28
				(3.65)
Baa rate				23.28
				(2.98)
Adjusted R^2	55%	68%	74%	84%
Percentage of $t \geq 1.96$ (β_1, historical volatility)	59%	56%	46%	47%
Percentage of $t \geq 1.96$ (β_2, implied volatility)	80%	78%	73%	57%
Percentage of $t \geq 1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 > \beta_1$)	57%	58%	47%	37%
Percentage of $t \leq -1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 < \beta_1$)	22%	21%	25%	29%

We notice that in the most exhaustive Regression 4, the firm-level implied volatility still comes up significant, with an average t-statistic of 3.07. In contrast, the firm-level historical volatility is only marginally significant, with an average t-statistic of 1.82. The cross-sectional distribution of t-statistics appears to be tighter for implied volatility than for historical volatility—the former has 57% of the 301 cases with t-statistics greater than 1.96, while the latter has only 47% 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). In

37% 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 29% of the cases.[6]

Further demonstrating the importance of implied volatility, the magnitude of the implied volatility coefficient is about three times as large as that of the historical volatility coefficient (2.01 vs. 0.69 in Regression 4). Given the cross-sectional averages of the time-series standard deviations of implied volatility and the 252-day historical volatility (7.55% and 9.08%, respectively), a one standard-deviation change in implied volatility causes a 15 basis point change in the CDS spread. In contrast, a one standard-deviation change in the 252-day historical volatility causes only a six basis point change in the CDS spread.

Overall, both the 252-day historical volatility and the option-implied volatility appear to 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 implied volatility dominates historical volatility in explaining the CDS spread.

4. The role of the volatility risk premium

Given the common perception of implied volatility as a "market consensus forecast" of forward-looking future volatility, perhaps it comes as no surprise that implied volatility best explains CDS spreads 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 context of individual stocks. Studies based on stock index options, such as Day and Lewis (1992) and Canina and Figlewski (1993), do not support implied volatility as an informationally efficient estimator of future volatility. On the other hand, Jiang and Tian (2005) find that the model-free implied volatility subsumes all information contained in the Black–Scholes implied volatility, as well as historical volatility in forecasting future realized volatility.[7] 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 the future realized volatility of 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 (2007) 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 premiums 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-series 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.

[6]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.

[7]Jiang and Tian (2005) point out that the model-free implied volatility aggregates information across options with different strike prices, and is therefore informationally more efficient than the Black–Scholes implied volatility extracted from at-the-money options. Since our implied volatility measure is computed across all put options with a non-zero open interest, it, too, aggregates information across a large number of options.

4.1. Implied volatility as a superior forecast of future volatility

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 we report the cross-sectional averages of the coefficients and their associated t-statistics. To allow for the influence of market-level volatilities, we also include the market implied and historical volatilities, defined earlier from S&P 500 index puts and S&P 500 index returns, respectively. The full regression model for each firm is therefore:

$$FV_t = \alpha + \beta_1 HV_t + \beta_2 IV_t + \beta_3(\text{mkt. hist. vol.})_t + \beta_4(\text{mkt. imp. vol.})_t + \varepsilon_t. \qquad (2)$$

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. Our results can be found in Table 4.

In univariate regressions, both historical volatility and implied volatility contain information for future realized volatility. For example, the average R^2 with historical (implied) volatility included as the sole explanatory variable is 25% (33%). However, with both included in the regression, implied volatility appears to dominate historical volatility in predicting future realized volatility. For example, Regression 3 shows that the coefficient of implied volatility (β_2) is significant for 79% of the obligors, as opposed to only 30% for historical volatility (β_1). Similarly, in 66% of the cases, we can reject the hypothesis of $\beta_1 = \beta_2$ in favor of $\beta_2 > \beta_1$, but in only 8% of the cases do we obtain the opposite result. The implied volatility coefficient is positive on average, but less than unity (0.65), while the

Table 4
Predictive regression of future realized volatility.

Cross-sectional averages of coefficients, t-statistics (in parentheses), and adjusted R-squares of time-series regressions for 301 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 the implied volatility of each individual firm, and the 84-day historical volatility and the implied volatility of the S&P 500 index. Newey and West (1987) standard errors (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006.

	1	2	3	4
Intercept	18.31	6.85	7.65	11.56
	(10.13)	(2.53)	(2.78)	(3.75)
Historical volatility (β_1)	0.39		0.02	−0.08
	(8.60)		(0.06)	(−0.85)
Implied volatility (β_2)		0.67	0.65	0.44
		(10.62)	(5.28)	(3.23)
Market historical volatility				0.09
				(0.46)
Market implied volatility				0.25
				(1.70)
Adjusted R^2	25%	33%	36%	45%
Percentage of $t \geq 1.96$ (β_1, historical volatility)	82%		30%	20%
Percentage of $t \geq 1.96$ (β_2, implied volatility)		89%	79%	59%
Percentage of $t \geq 1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 > \beta_1$)			66%	56%
Percentage of $t \leq -1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 < \beta_1$)			8%	13%

Table 5
Summary statistics of predicted future volatility and volatility risk premium.

Cross-sectional summary statistics of the time-series mean, standard deviation, and correlation of the implied volatility (*IV*), predicted future volatility (*FV*), and volatility risk premium for 301 sample firms. The predicted *FV* is the fitted value from the predictive regression of future realized volatility on firm-level and market-level historical volatility and implied volatility (Specification 4 of Table 4). The volatility risk premium is defined as the difference between *IV* and the predicted *FV*. The sample period extends from January 2001 through December 2006.

	Mean	Q1	Median	Q3
μ (*IV*)	34.82	28.38	33.00	39.06
μ (predicted *FV*)	30.69	23.56	28.92	35.28
μ (volatility risk premium)	4.13	2.80	4.21	5.47
σ (*IV*)	7.55	4.46	6.39	8.69
σ (predicted *FV*)	7.06	3.24	5.52	7.89
σ (volatility risk premium)	4.49	2.55	3.45	4.87
ρ (*IV*, predicted *FV*)	0.73	0.65	0.87	0.94
ρ (*IV*, volatility risk premium)	0.46	0.17	0.59	0.83
ρ (predicted *FV*, volatility risk premium)	−0.10	−0.51	−0.15	0.28

intercept is positive on average (7.65). These results suggest that implied volatility is a biased estimator for future volatility. In Regression 4, we find that the market implied volatility is marginally useful in predicting firm-level future volatility—the average R^2 increases from 36% to 45%. Combining these results, we conclude that individual firm-implied volatility is a more efficient (even though biased) forecast for future realized volatility than historical volatility.

4.2. Effect of the volatility risk premium on the CDS spread

Next, we study the effect of a time-varying volatility risk premium on CDS spreads. We define the volatility risk premium as $IV-\widehat{FV}$, where $\widehat{FV}$ is the predicted value of future volatility, based on the estimation of Eq. (2) over the full sample. As Table 5 shows, the average time-series means of IV and $\widehat{FV}$ are 34.82% and 30.69%, respectively. Thus the implied volatility is, on average, greater than the predicted future volatility. The average time-series standard deviations of IV and $\widehat{FV}$ are 7.55% and 7.06%, respectively. The average time-series correlation between IV and $\widehat{FV}$ is only 0.73. Therefore, the predicted future volatility is almost as volatile as the implied volatility; moreover, they are imperfectly correlated. Consequently, the volatility risk premium is not merely reflecting the information content of implied volatility for explaining CDS spreads; rather, the average time-series correlation between $IV-\widehat{FV}$ and $\widehat{FV}$ is only −0.10, suggesting that the information contained in each variable is unique.

We include both $\widehat{FV}$ and $IV-\widehat{FV}$ in lieu of IV and HV in a CDS spread regression of the type in Eq. (1).[8] Compared to our benchmark regression results in Table 3, Panel A of Table 6

[8]To the extent that $\widehat{FV}$ is an imperfect measure of the true conditional expected future volatility, the estimated coefficients are subject to an errors-in-variables problem. This is discussed in the Appendix. We have also experimented with alternative proxies for the expected future volatility, such as the historical volatility (*HV*), with similar results.

Table 6
Time-series regression analysis of CDS spreads on predicted future volatility and volatility risk premium.

Cross-sectional averages of coefficients and *t*-statistics (in parentheses) of time-series regressions for 301 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 are the predicted *FV*, volatility risk premium, and other firm-level and market-level variables defined in Table 1. The predicted *FV* is the fitted value from the predictive regression of future realized volatility on firm-level and market-level historical volatility and implied volatility (Specification 4 of Table 4). The volatility risk premium is defined as the difference between *IV* and the predicted *FV*. The rescaled volatility risk premium (%) is the ratio of the volatility risk premium over the predicted *FV*. Newey and West (1987) standard errors (with five lags) are used to compute *t*-statistics. The sample period extends from January 2001 through December 2006. Regressions 1–4 are similarly defined as in Table 3. For simplicity, only the coefficients and *t*-statistics of the predicted *FV* and the volatility risk premium are reported.

	1 No control	2 Firm-level control	3 Market-level control	4 All controls
Panel A: Standard volatility risk premium				
Predicted *FV*	4.96	2.97	2.95	1.51
	(12.33)	(8.36)	(8.26)	(2.15)
Volatility risk premium	5.24	3.15	3.16	2.07
	(8.21)	(5.70)	(5.70)	(2.90)
Firm- and market-level control variables	–	–	–	–
Panel B: Rescaled Volatility Risk Premium				
Predicted *FV*	5.63	3.23	3.21	1.50
	(12.23)	(8.34)	(8.27)	(2.03)
Volatility risk premium/predicted FV	1.77	0.90	0.91	0.58
	(7.44)	(5.35)	(5.35)	(2.62)
Firm- and market-level control variables	–	–	–	–

shows that the coefficient of $\widehat{FV}$ is much larger than the coefficient of HV. It is also statistically more significant, suggestive of a tight relation between the CDS spread and the expected future volatility, given the right volatility forecast. For example, Regression 4 of Table 6 shows that the coefficient of $\widehat{FV}$ is 1.51, with a *t*-statistic of 2.15. In contrast, Regression 4 of Table 3 shows that the coefficient of historical volatility is only 0.69, with a *t*-statistic of 1.82. Most notable, however, is the coefficient of the volatility risk premium, which remains highly significant in the presence of $\widehat{FV}$. In Regression 4, where we have included all firm-level and market-level control variables, the volatility risk premium is highly significant, with a coefficient of 2.07 and a *t*-statistic of 2.90. These results are qualitatively the same when we define a rescaled version of the volatility risk premium as $(IV-\widehat{FV})/\widehat{FV}$ (see Panel B of Table 6).

In summary, to model the CDS spread properly, it is crucial to (1) have an accurate description of the dynamics of volatility under the objective measure, and (2) incorporate a time-varying volatility risk premium. Our evidence suggests that each of these considerations is crucial to explaining CDS spreads.

5. Robustness results

5.1. Alternative measures of credit market illiquidity

Instead of using the Feldhütter and Lando (2008) Treasury convenience yield factor as a proxy of credit market illiquidity, which is derived from a parametric model of the

Table 7
The impact of alternative credit market illiquidity measures.

Cross-sectional averages of coefficients, t-statistics (in parentheses), and adjusted R-squares of time-series regressions for 301 sample firms with alternative credit market illiquidity measures as control variables. The first illiquidity measure is the liquidity component of the swap spread based on Feldhütter and Lando (2008). The second illiquidity measure is the difference between 10-year swap and 10-year U.S. Treasury yields. The third illiquidity measure is the difference between 10-year on-the-run and first off-the-run treasury yields. For each firm and each time-series regression, the dependent variable is the daily five-year composite credit default swap spread. The definitions of other independent variables are provided in Table 1. Newey and West (1987) standard errors (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006. For simplicity, only the coefficients and t-statistics of the volatility and illiquidity measures are reported.

	1	2	3
Intercept	−340.77	−328.90	−351.09
	(−5.20)	(−4.96)	(−5.52)
Historical volatility (β_1)	0.69	0.32	0.37
	(1.82)	(1.40)	(1.38)
Implied volatility (β_2)	2.01	2.14	2.18
	(3.07)	(3.48)	(3.54)
Illiquidity measures			
Credit market illiquidity (1)	93.28		
	(3.65)		
Credit market illiquidity (2)		30.94	
		(1.42)	
Credit market illiquidity (3)			−0.02
			(1.02)
Firm- and market-level control variables	–	–	–
Adjusted R^2	84%	83%	83%
Percentage of $t \geq 1.96$ (β_1, Historical volatility)	47%	41%	41%
Percentage of $t \geq 1.96$ (β_2, Implied volatility)	57%	61%	63%
Percentage of $t \geq 1.64$ (H$_0$: $\beta_2 = \beta_1$ vs. H$_1$: $\beta_2 > \beta_1$)	37%	45%	43%
Percentage of $t \leq -1.64$ (H$_0$: $\beta_2 = \beta_1$ vs. H$_1$: $\beta_2 < \beta_1$)	29%	27%	26%

swap-Treasury spread, we consider alternative measures that are model-independent and check whether they alter our main results. The first alternative measure we use is the swap-Treasury spread itself, which has a tendency to increase during a credit market liquidity crunch. As shown by Feldhütter and Lando (2008), the swap-Treasury spread contains both liquidity risk and credit risk components, as well as a swap-specific component related to hedging activities in the mortgage-backed securities market. However, they show that the liquidity component is by far the largest and most variable part of the swap-Treasury spread. Of course, using the swap-Treasury spread itself spares us from estimation errors, because we are not filtering the data through any particular model. The second model-independent measure we use is the difference between 10-year on-the-run and first off-the-run Treasury yields, following the methodology of Fleming (2003), which has been used by numerous other studies (see Fleming, 2003, for additional references).[9]

Table 7 presents estimation results using each of the three credit market illiquidity measures. While our original illiquidity measure is positive and significant, the coefficient of the swap-Treasury spread (and the coefficient of the difference between on-the-run and

[9]Specifically, of all Treasury securities issued as 10-year bonds, we designate the most recently issued as the ''on-the-run'' issue and the second most recently issued as the ''first off-the-run'' issue.

Table 8
Time-series regression analysis of CDS spreads on predicted future volatility and volatility risk premium (out-of-sample approach).

Cross-sectional averages of coefficients and t-statistics (in parentheses) of time-series regressions for 301 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 are the predicted future volatility (FV), volatility risk premium, and other firm-level and market-level variables defined in Table 1. To construct out-of-sample estimates of future volatility, we adopt the following steps for each firm. (1) On date t, only the information up to t is used to estimate the predictive regression of future realized volatility on firm-level and market-level historical volatility and implied volatility; (2) On date t, we compute the predicted FV by using the regression coefficients from step 1 and the date t firm-level and market-level historical volatilities and implied volatilities; (3) We then compute volatility risk premium as the difference between implied volatility and the predicted FV from step 2. The rescaled volatility risk premium (%) is the ratio of the volatility risk premium over the predicted FV. Newey and West (1987) standard errors (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006. Regressions 1–4 are similarly defined as in Table 3. For simplicity, only the coefficients and t-statistics of the predicted FV and volatility risk premium are reported.

	1 No control	2 Firm-level control	3 Market-level control	4 All controls
Panel A: Standard volatility risk premium				
Predicted FV	4.29	2.53	2.50	1.72
	(11.23)	(6.72)	(6.72)	(2.66)
Volatility risk premium	4.01	2.38	2.35	1.74
	(9.38)	(6.23)	(6.23)	(2.74)
Firm- and market-level control variables	–	–	–	-
Panel B: Rescaled volatility risk premium				
Predicted FV	3.63	1.88	1.82	1.01
	(8.71)	(5.24)	(5.21)	(1.76)
Volatility risk premium/predicted FV	1.04	0.53	0.52	0.26
	(6.17)	(4.48)	(4.47)	(1.97)
Firm- and market-level control variables	–	–	–	–

first off-the-run Treasury yields) is, on average, insignificant. More importantly, we find that the coefficient of implied volatility remains qualitatively unchanged when we adopt the alternative credit market illiquidity measures. For example, the average coefficients of implied volatility are 2.01, 2.14, and 2.18, and the associated average t-statistics are 3.07, 3.48, and 3.54, across the three illiquidity measures. Overall, the relation between the CDS spread and implied volatility becomes somewhat stronger, and the relation between the CDS spread and historical volatility becomes somewhat weaker, when we use the alternative illiquidity measures.[10]

5.2. *Effect of the volatility risk premium: out of sample results*

The construction of our volatility risk premium measure relies on an estimation of the predicted future volatility using the entire sample period. Therefore, it is not truly an out-of-sample forecast. To eliminate this more subtle source of look-ahead bias from our

[10]We repeat the other parts of our analysis using the two alternative illiquidity measures, and find qualitatively similar results. These additional results are available upon request.

empirical procedure, we adopt an alternative estimation approach. For each day t, we use market data up to t to estimate Eq. (2). Specifically, because we require at least 84 days of observed stock returns to compute FV, we estimate Eq. (2) over a sample period that starts in January 2001 and ends at t-84. In addition, we begin the estimation in January 2002 because it would give us at least 12 months of data for this estimation. We then use the observed market data on day t to construct the expected future volatility over the next 84 trading days. Table 8 shows that our previous results remain robust under this alternative methodology.

5.3. Historical volatilities with alternative horizons

In our preceding analysis, we compared the information content of implied volatility to that of the 252-day historical volatility for explaining CDS spreads. Here, we present evidence for 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 9, we present the benchmark regression using different historical volatility estimators. The implied volatility coefficient remains quite stable in its size as well as statistical significance. In comparison, 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. Then, as the estimation horizon further shrinks to 63 days or 22 days, it 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 126-day historical volatility in the benchmark regressions, its average coefficient is 0.89, while the average implied volatility coefficient is 1.82.

What do we make of these additional findings? Clearly, long-horizon (e.g., 1,000-day) 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 important credit events that are reflected in CDS spreads. On the other hand, short-horizon (e.g., 22-day) 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. We therefore conclude that the information advantage of implied volatility is robust to historical volatility estimators of different horizons.

5.4. Sub-sample results

Because our sample consists of a broad cross-section of firms, we can analyze how the information content of implied volatility for CDS pricing depends on important firm-level characteristics. According to Black (1975), Back (1993), Easley et al. (1998), and others, implied volatility is likely to be informative when the options have sufficient leverage and liquidity, as well as when the amount of information asymmetry in the options market is high. Recent empirical studies, such as Cao et al. (2005) and Pan and Poteshman (2006), have tested these predictions by examining the predictive power of the option volume for future stock returns.

Table 9
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 301 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 (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006.

	Historical volatility				
	22-day	63-day	126-day	252-day	1000-day
Intercept	−329.04	−278.50	−279.93	−340.77	−221.91
	(−5.38)	(−5.23)	(−5.22)	(−5.20)	(−4.46)
Historical volatility (β_1)	0.17	0.36	0.89	0.69	0.66
	(0.98)	(1.65)	(2.06)	(1.82)	(1.43)
Implied volatility (β_2)	2.01	1.89	1.82	2.01	2.08
	(3.25)	(2.68)	(2.70)	(3.07)	(3.64)
Additional firm-specific variables					
Implied volatility skew	5.04	5.04	5.16	5.09	4.99
	(0.46)	(0.46)	(0.39)	(0.53)	(0.52)
Leverage ratio	3.64	3.11	2.98	3.64	3.04
	(2.78)	(2.63)	(2.63)	(2.63)	(2.64)
Firm stock return	−0.02	−0.03	−0.03	0.00	−0.03
	(−0.26)	(−0.39)	(−0.23)	(−0.12)	(−0.28)
Market volatility variables					
Market historical volatility	1.50	1.51	1.11	1.09	1.43
	(1.38)	(1.14)	(0.62)	(0.03)	(0.72)
Market implied volatility	−0.42	−0.26	−0.16	−0.31	−0.26
	(−0.74)	(−0.46)	(−0.32)	(−0.47)	(−0.59)
Market implied volatility skew	−2.27	−1.16	−1.31	−2.10	−0.72
	(0.30)	(0.37)	(0.36)	(0.26)	(0.31)
Macro variables					
Stock market return	0.05	−0.02	0.01	0.05	0.02
	(1.10)	(0.91)	(1.02)	(1.21)	(1.19)
Treasury rate	−24.83	−22.60	−24.65	−23.60	−22.53
	(−3.22)	(−2.92)	(−3.31)	(−3.24)	(−3.22)
Yield curve slope	−14.86	−13.62	−14.06	−14.58	−12.26
	(−2.32)	(−2.06)	(−2.30)	(−2.15)	(−2.53)
Credit market illiquidity	94.54	90.49	81.91	93.28	91.42
	(3.72)	(3.36)	(3.05)	(3.65)	(3.02)
Baa rate	24.91	22.21	23.96	23.28	19.95
	(3.24)	(3.06)	(3.22)	(2.98)	(3.02)
Adjusted R^2	83%	83%	84%	84%	83%
Percentage of $t \geq 1.96$ (β_1, Historical volatility)	32%	48%	51%	47%	42%
Percentage of $t \geq 1.96$ (β_2, Implied volatility)	62%	59%	54%	57%	63%
Percentage of $t \geq 1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 > \beta_1$)	59%	47%	41%	37%	40%
Percentage of $t \leq -1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 < \beta_1$)	9%	18%	26%	29%	31%

To the extent that options market liquidity is proxied by open interest and trading volume, and the degree of information asymmetry increases with the volatility of the CDS spread and decreases with credit rating, we create sub-samples by sorting on these firm-level characteristics and summarize the regression results for each sub-sample. Indeed, results not presented here confirm that the information content of implied volatility for

CDS pricing is greater among firms with lower credit ratings, higher CDS spread volatilities, and more actively traded options. These results are available upon request.

5.5. Lead-lag relation between options and CDS markets

So far, we have focused on the contemporaneous relation between the CDS spread and firm-level volatility measures. The recent studies of Acharya and Johnson (2007) and Berndt and Ostrovnaya (2008) analyze the lead-lag relation among stock, CDS, and options markets around abrupt changes in CDS spreads or corporate news announcements. Using their methodology, we examine the unconditional flow of information between the options market and the CDS market, which can shed further light on the information content of implied volatility for CDS valuation. Our results (available upon request) identify a robust predictability of future CDS spread changes from current implied volatility innovations. Interestingly, the predictability in the opposite direction appears much weaker. Overall, our results support the notion that the individual stock options market plays a significant role in the price discovery process, even in the presence of a competing venue such as the credit derivatives market.

5.6. Including financial firms

In our regression analysis of CDS pricing, we have followed standard practice to eliminate financial firms from our sample. To the extent that financial firms have more complex capital structures, a simple leverage ratio based on total liabilities may not be a useful explanatory variable for the credit spread. Nevertheless, we have identified 70 financial firms in our sample period and have repeated the benchmark regression with a total of 371 firms, including the original sample of 301 non-financial firms along with the 70 financial firms. As shown in Table 10, the changes in the estimated coefficients are marginal. Our results can therefore be generalized to financial firms.

6. 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? What is the role of the volatility risk premium in the relation between CDS spreads and option-implied volatility? These are the key questions addressed by our 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. 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, suggesting 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 regressions, we find that implied volatility dominates historical volatility in explaining CDS spreads; the coefficient of implied volatility is larger and more significant than the coefficient of historical volatility for the majority of the firms in our sample. More importantly, we conduct predictive regressions of future volatility on the implied and historical volatilities of individual stocks. We find implied volatility to be a

Table 10
Time-series regression analysis of CDS spreads—including financial firms.

Cross-sectional averages of coefficients, t-statistics (in parentheses), and adjusted R-squares of time-series regressions for 371 firms (301 original sample firms and 70 additional financial 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 (with five lags) are used to compute t-statistics. The sample period extends from January 2001 through December 2006.

	1	2	3	4
Intercept	−73.93	−189.18	−180.19	−332.62
	(−6.11)	(−5.71)	(−4.99)	(−4.86)
Historical volatility (β_1)	1.06	0.91	0.42	0.61
	(3.21)	(2.56)	(1.54)	(1.58)
Implied volatility (β_2)	3.98	2.86	2.66	1.86
	(7.97)	(6.28)	(4.81)	(3.06)
Additional firm-specific variables				
Implied volatility skew		7.64	6.20	4.34
		(1.14)	(0.83)	(0.53)
Leverage		2.66	2.34	3.41
		(4.66)	(3.24)	(2.58)
Firm stock return		−0.03	−0.03	−0.01
		(−0.31)	(−0.18)	(−0.05)
Market volatility variables				
Market historical volatility			1.99	1.10
			(1.26)	(0.17)
Market implied volatility			0.12	−0.28
			(1.04)	(−0.41)
Market implied volatility skew			3.54	−1.78
			(0.87)	(0.17)
Macro variables				
Market return				0.06
				(1.01)
Treasury rate				−24.01
				(−3.49)
Yield curve slope				−13.54
				(−2.03)
Credit market illiquidity				94.63
				(3.74)
Baa rate				24.20
				(3.11)
Adjusted R^2	54%	68%	75%	85%
Percentage of $t \geq 1.96$ (β_1, Historical volatility)	57%	55%	44%	46%
Percentage of $t \geq 1.96$ (β_2, Implied volatility)	80%	78%	74%	57%
Percentage of $t \geq 1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 > \beta_1$)	58%	57%	49%	38%
Percentage of $t \leq -1.64$ (H_0: $\beta_2 = \beta_1$ vs. H_1: $\beta_2 < \beta_1$)	22%	22%	24%	29%

more efficient (but biased) forecast of future stock return volatility; for the majority of the obligors, implied volatility subsumes 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 feature 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.

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Appendix A

A.1. Estimation bias of regressing CDS spread on $\widehat{FV}$ and $IV-\widehat{FV}$

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

$$y = \beta_1 x_1^* + \beta_2 x_2^* + \varepsilon, \tag{3}$$

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

$$x_1 = x_1^* + u, \quad x_2 = x_2^* - u, \tag{4}$$

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

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

$$\begin{aligned}\text{plim}\, b &= \text{plim}\left[\frac{1}{n}\begin{pmatrix} x_1'x_1 & x_1'x_2 \\ x_2'x_1 & x_2'x_2 \end{pmatrix}\right]^{-1} \text{plim}\frac{1}{n}\begin{pmatrix} x_1'y \\ x_2'y \end{pmatrix} \\ &= \begin{pmatrix} Q_1 + \sigma_u^2 & \rho\sqrt{Q_1Q_2} - \sigma_u^2 \\ \rho\sqrt{Q_1Q_2} - \sigma_u^2 & Q_2 + \sigma_u^2 \end{pmatrix}^{-1} \begin{pmatrix} \beta_1 Q_1 + \beta_2\rho\sqrt{Q_1Q_2} \\ \beta_2 Q_2 + \beta_1\rho\sqrt{Q_1Q_2} \end{pmatrix},\end{aligned} \tag{5}$$

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

$$b_1 = \beta_1 + \frac{(Q_2 + \rho\sqrt{Q_1Q_2})\sigma_u^2}{(1-\rho^2)Q_1Q_2 + (Q_1 + Q_2 + 2\rho\sqrt{Q_1Q_2})\sigma_u^2}(\beta_2 - \beta_1), \tag{6}$$

$$b_2 = \beta_2 + \frac{(Q_1 + \rho\sqrt{Q_1 Q_2})\sigma_u^2}{(1-\rho^2)Q_1 Q_2 + (Q_1 + Q_2 + 2\rho\sqrt{Q_1 Q_2})\sigma_u^2}(\beta_1 - \beta_2). \tag{7}$$

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. It disappears as the measurement error approaches zero.

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