CDS Inferred Stock Volatility

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Both CDS and out-of-money put option can protect investors against downside risk, so they are related while are not mutually replaceable. This study provides a straightforward linkage between corporate CDS and equity option by inferring stock volatility from CDS spread and, thus, enables a direct analogy with the implied volatility from option price. I find CDS inferred volatility (CIV) and option implied volatility (OIV) are complementary, both containing some information that is not captured by the other. CIV dominates OIV in forecasting stock future realized volatility. Moreover, a trading strategy based on the CIV-OIV mean reverting spreads generates significant risk-adjusted return. These findings complement existing empirical evidence on cross market analysis.

JEL classification: E44, G11, G12, G14

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1 Introduction

A CDS (credit default swap) is a contract in which the buyer of protection makes a series of payments (often referred to as CDS spreads) to the protection seller and, in exchange, receives a payoff if a default event occurs. A put option gives the buyer the right to buy the underlying asset at a pre-determined strike price. Therefore CDS and put option are related in that both protect investors against downside risk. For example, Cao, Yu and Zhong (2010) find put option implied volatility, dominating historical volatility, is a determinant of CDS spreads. Carr and Wu (2007, 2009) propose a joint valuation framework to estimate option prices and CDS spreads based on their covariation. Carr and Wu (2010) further develop a link to infer the value of a unit recovery claim (URC) from put and CDS spread, the authors find that the two markets show strong co-movements and the estimated URC have similar magnitudes.

However, there lacks a direct comparable measure. Most studies research on the relation between put prices (or implied volatilities) and CDS spreads. Investors have no clear clue what a 30% put implied volatility means for the reference entity's CDS spread, or vice versa, what is the implication of 50 bps CDS spread for the associated put option. The breakthrough URC in Carr and Wu (2010) provides a measure to compare the magnitudes between put and CDS, nevertheless, the unobservable and indirect URC has to be computed for both types of assets and thus restricts its many applications.

To fill this gap, in this paper I develop a procedure to infer stock volatility from corporate CDS spread. According to the Merton (1974) distance to default model, a firm's stock volatility determines the distance to default and the default probability, with other variables such as market value of equity and face value of debt observed. So conversely for a given default probability, we are able to back out the stock volatility. Based on a standard CDS valuation model, implied default probability can be easily estimated for a given CDS spread. Therefore I first compute the implied default probability from CDS spreads, and then fit and calibrate the Merton (1974) model to solve the stock volatility, called CDS inferred volatility (CIV). Since there is one unique default probability both for a given CDS spread and for a given volatility, there must be one-to-one correspondence between CDS spread and CIV. The estimated CIV can then be used directly as a firm indicator.

Faust, et al. (2013) predict real-time economic activity with credit spreads and the gains by including credit information are both statistically and economically significant. This ex ante perspective of CDS spreads indicates our CIV is also forward-looking. By applying the method on weekly US corporate CDS from January 2001 to December 2011, I find three main results. First, CIV and option implied volatility (OIV) are mutually complementary. On average the sample correlation between CIV and OIV is 11.63%. CIV significantly explains OIV. A univariate regression of OIV on CIV indicates that, on average, CIV explains 14.46% of the variation of OIV. The explanatory power is stronger for junk-grade firms (15.12% adjusted R^2) than for investment-grade firms (12.76% adjusted R^2). The coefficient of CIV is 0.4973 for investment-grade firms and is 0.9849 for junk-grade firms. On the other hand, OIV is also a significant explanatory variable for CIV. The intercepts for both regressions are significant at the 1% level, robust to controlling for other option characteristics such as the Delta, open interest and maturity. This finding suggests our CIV highly relates to

OIV, nevertheless, there is some information in option market that is not captured by CDS market, and vice versa.

Second, CIV predicts stock future realized volatility, it is a more efficient forecast than OIV. By regressing future realized volatility on historical volatility, OIV and / or CIV, I find both OIV and CIV are significantly positive, and CIV has a better predictability. Specifically, the combination of historical volatility and CIV explains 20.90% of the variation of future realized volatility while the combination with OIV explains 18.32% when the whole sample is used. CIV has a better performance for both investment- and junk-group firms. When adding both OIV and CIV into regression, the adjusted R^2 increases to 30.00% and the sign and significance keep similar, suggesting the two variables have their relative merits. The coefficient estimate for CIV is larger and closer to one, indicating that CIV is a more efficient forecast than OIV.

Third, a trading strategy on the spread between CIV and OIV generates significant risk adjusted returns. Carr and Wu (2010) find the URC values estimated from CDS and option markets deviate from each other and tend to converge later, this convergence predicts future movements in both markets. In this study I examine the co-integration between CIV and OIV, if their linear relationship is stationary and mean reverting, we are able to explore their temporary deviations and sequential reversion. I find the CIV and OIV are co-integrated for 92% of the firms at the 10% significance level in my sample during the whole periods. I then divide CDSs into four Quartile groups by the CIV-OIV spread z-scores. The first group consists of the 25% CDSs with the smallest z-scores and the fourth group consists of the 25% CDSs with the largest z-scores. Every week I long the CDSs in the first Quartile group and short the CDSs in the fourth Quartile group, hold the portfolio for one week and rebalance if necessary. This simple trading strategy from April 2005 to December 2011, without accounting for transaction costs, generates an annualized return (Sharpe ratio) of 17.31% (2.0224), compared with the 8.96% (0.2452) of the buy-and-hold strategy. In addition, the long-short strategy suffers much less during the financial crisis and has a much smaller Maximum drawdown.

Overall this study contributes to the literature in the following aspects. Firstly, it provides a straightforward measure to convert corporate CDS spread to stock volatility, facilitating analogy across markets. This CIV measure complements the URC measure in Carr and Wu (2010). Secondly, it provides additional evidence on the price discovery and interaction among CDS, stock and option markets. Forte and Pena (2013) investigate the dynamic relationship between stock, CDS and bond markets and find stocks lead CDS, which on the other hand leads bonds. On the contrary, Berndt and Ostrovnaya (2008) find both CDS and option markets lead stock market. My evidence suggests both CDS and option market contains useful information to predict the variation of stock market, and it seems option market dominates CDS credit market. Thirdly, it complements other studies on the predictability of CDS spreads. Faust, et al. (2013) use credit spreads to forecast economic activity including real GDP, real personal consumption expenditures (PCE), etc. Friewald, Wagner and Zechner (2014) find firms' stock return is linked with credit risk premia estimated from CDS spreads. Han and Zhou (2011) predict future stock returns with the slope of the term structure of CDS spreads. Different from their efforts to forecast the level of stock market (the first moment), this study examines the CDS predictability on the variation of stock market (the second moment). Lastly, as a complement to the CDS trading strategy exploring relative mispricing in the term structure of CDS spreads in Jarrow, Li and Ye (2011), this study designs a simple strategy by exploring the temporary disjoint movement between CDS and option market. This strategy has a nice risk reward profile and provides insights to practitioners.

The rest of this study is as follows. Section 2 introduces the methodology to extract CIV. Section 3 explains the CDS, stock and option data. Section 4 presents the empirical results and section 5 concludes.

2 CIV estimation methodology

In this section I introduce the methodology to infer underlying stock volatility from CDS spread. I first present a CDS valuation model in which the only uncertain input is default probability, then I describe the Merton (1974) distance to default model in which the default probability can be computed for a given stock volatility. Equating the two default probability enables me to back out volatility, called CIV in this paper.

2.1 CDS valuation

A CDS is a swap contract and agreement in which the protection buyer of the CDS makes a series of payments to the protection seller and in exchange, receives a payoff in the event of default. Let s be CDS spread which is the amount as a percentage of the notional principal, T be the maturity of a CDS contract, π_s be the default probability of a reference entity during a year conditional on no earlier default, r be the continuous compounding risk-free rate, and the present value of the premium leg of a CDS can be written as

$$\sum_{t=1}^{t=T} (1-\pi_s)^t e^{-rt} s + (1-\pi_s)^{t-1} \pi_s e^{-r(t-0.5)} 0.5s \tag{1}$$

wherein following Bharath and Shumway (2008) and others, we assume that default only occurs during the second half of a year and s is paid once per year. The first term is the discounted present value of expected payments if there is no default before date t, the second term is the present value of accrual payments if default occurs.

Similarly, if a default event occurs then the protection seller pays the buyer the par value and in return gets a bond issued by the same reference entity, the present value of the protection leg of a CDS is

$$\sum_{t=1}^{t=T} (1-\delta)(1-\pi_s)^{t-1} \pi_s e^{-r(t-0.5)} \tag{2}$$

with δ being the recovery rate of the par value in the event of default, we assume δ=0.4 in this study and other reasonable value does not change our conclusion qualitatively (Longstaff, Mithal, and Neis, 2005; Bharath and Shumway, 2008).

At date t, the only unobservable parameter is π_s. Since the present values of both legs should be equal to avoid arbitrage, we can solve for π_s by equating (1) and (2) for a given s, T and r.

2.2 Merton distance to default model

The effectiveness of Merton (1974) model has been examined by Bharath and Shumway (2008), in which the authors conclude that the Merton (1974) functional form is especially useful for forecasting defaults. The Merton model assumes the total value of a firm follows geometric Brownian motion

$$dV = \mu V dt + \sigma_V dW \tag{3}$$

where V is the total value of the firm, μ and σ_V are the expected return and volatility of the firm value, dW is a Wiener process. Treating the equity of the firm as a call option on the firm value with a strike price equal to the face value of the firm's debt maturing at T, the equity value E can be calculated by the Black-Scholes option pricing formula

$$\begin{gathered} E = VN\left(d_1\right) - e^{-rT} DN\left(d_2\right) \\ d_1 = \frac{\ln\left(\frac{V}{D}\right) + \left(r + 0.5\sigma_V^2\right) T}{\sigma_V \sqrt{T}} \\ d_2 = d_1 - \sigma_{\mathrm{V}} \sqrt{\mathrm{T}} \end{gathered} \tag{4}$$

where D is the face value of debt, N() is the cumulative standard normal distribution.

Further, since the value of equity E is a function of the firm value V, we know by Ito's lemma that

$$\sigma_E = \frac{V}{E} \frac{\partial E}{\partial V} \sigma_V = \frac{V}{E} N\left(d_1\right) \sigma_V \tag{5}$$

The distance to default can be calculated as

$$\mathrm{DD} = \frac{\ln\left(\frac{V}{D}\right) + \left(\mu - 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{6}$$

Merton (1974) then forecasts the default probability as

$$\pi_{Merton} = N\left(-DD\right) \tag{7}$$

At date t, the values of E and D are observable, so for a given and stock volatility σ_E, we are able to solve σ_V and V numerically using the two non-linear Eq. (4) and (5), which are used to estimate the default probability in Eq. (7). As a consequence, there is a unique relation between σ_E and π_{Merton} . Conversely, assuming the CDS implied default probability in Section 2.1 is an unbiased estimator of the default probability in Merton (1974) model, we can back out a unique value σ_E given any CDS spread s numerically. The extracted σ_E via the above procedures is the CIV in this study.

3 Sample data selection

I obtain weekly mid-quotes 5-year constant maturity USD-denominated corporate CDSs on every Wednesday from January 2002 to December 2011 from the Markit Company, who collects and aggregates data from industry sources. I include only those CDSs satisfying the following two screening criteria: first, the CDS must have at least one-year trading data; second, it must have a modified restructuring (MR) clause. The first criterion excludes any

CDS that disappears soon after being listed or is issued recently. The second criterion is applied because a restructuring clause can change the recovery rate in the event of a default and thus, various clauses may have differential effects on the CDS spread valuation method.

I then match the CDS reference entity list with the option data provided by OptionMetrics, who collects option trading prices, volumes, etc., and estimates the implied volatilities and Greeks. For my analysis purpose on out-of-money put option and analogous to Cao, Yu and Zhong (2010) and Carr and Wu (2010), I require the put options to have positive bid price, bid ask spread, trading volume, open interest, and implied volatility. In addition, the absolute value of the put's delta should not be larger than 15% to be out of money. After the above filtering, on each observation date, if a firm has several put options with the same maturity, I use the one with the highest open interest; and if a firm still has multiple put options with different maturities, I choose the put with the longest maturity. Option with the highest open interest is the most liquid, and option with the longest maturity has minimum maturity mismatch with the corresponding CDS[1].

I use the 1-year Treasury constant maturity rate obtained from the Federal Reserve Board as the risk-free rate. To compute the equity and debt values for each firm, I match the reference entity list with the CRSP and COMPUSTAT database. Equity value E is calculated as the product of share price at date t and the number of shares outstanding, debt value D is the sum of current liabilities and one-half of long-term debt (Vassalou and Xing, 2004). The expected return of the firm value μ is assumed to equal to the risk-free

[1] I could obtain 1-, 2-, 3-, and 5-year CDS spreads from the Markit company and linearly interpolate to match exactly with option maturity, however, as an argument shared in Carr and Wu (2010), 5-year CDS is the most reliable and traded contract. In addition, not all reference entities have valid CDS spreads other than the five year maturity. Doing so would therefore dramatically decrease the number of firms in sample.

rate. Campbell, Hilscher and Szilagyi (2008) use instead μ=r+6% in their default research, my additional analysis shows it does not change the findings in this study.

Table 1 reports the data summary statistics. There are some extreme values in the COMPUSTAT data, I winsorize equity and debt values for each firm by setting all observations larger than the 99th percentile or smaller than the 1st percentile to that value. After the above filtering, my final sample includes 363 firms crossing 514 weeks; the total number of observations is 91,821 so that, on average, each firm has 253-week valid CDS and option data, and the number of observations for a firm ranges from 52 to 514 weeks. The maturity for the put options ranges from 3 to 969 days, with an average of 286 days.

4 Empirical results and discussion

Applying the methodology in Section 2 on the sample data described in Section 3, I summarize the inferred volatility in Table 1. CIV and OIV have similar mean values (42.51% vs. 44.72%), however, CIV has a much smaller standard deviation than OIV (10.88% vs. 20.11%), suggesting that CIV estimates are more persistent. Both the positive averaged sample correlations between CDS spread and CIV, and between CIV and OIV are expected, as intuitively a larger CDS spread means a higher default probability, which is reflected by an increase of inferred volatility and option premium (implied volatility).

4.1 Relation between CIV and OIV

The 11.63% sample average correlation between CIV and OIV suggests these two variables are related. In this section I first run a time series regression of OIV on CIV for each firm to further examine their relation,

$$OIV_{i,t} = \alpha_i + \beta_i \times CIV_{i,t} + \beta_i^{CV} \times CV_{i,t} + \varepsilon_{i,t}, i = [1, 2, ...N] \tag{8}$$

where CV is the control variables (the option Delta, open interest and maturity), N is the total number of firms. Then I conduct a t-test on the significance of α_i and β_i. If CIV and OIV are mutually replaceable, we would expect that α_i=0 and β_i=1.

Table 2 reports the regression results. Panel A, B, and C is for the test when only the investment-grade firms (BBB and above credit rating), only the junk-grade firms (BB and below credit rating) and the whole sample firms are used, respectively. The t-statistic is computed based on the method in Collin-Dufresne, Goldstein, and Martin (2001) to capture the cross-sectional variation in the time-series regression coefficient estimates. It is calculated by dividing each averaged coefficient value by the standard deviation of the N estimates and multiplying $\sqrt{N}$.

CIV significantly explains the variation of OIV at the 1% level. The adjusted R^2 is 14.46% when the whole sample is used. CIV has a better performance in explaining OIV for junk-grade firms than for investment-grade firms, with an adjusted R^2 15.12% vs. 12.76%. The constant term α_i is also highly significant at the 1% level, suggesting that OIV contains some information that is not captured by CIV.

To test whether CIV contains information that OIV does not. I re-run the whole regression of CIV on OIV, and report the results in Table 3. Consistent with those in Table 2, both the constant and coefficient estimates are highly significant. The coefficient for OIV is 0.0377, far away from one. Taken the results in Table 2 and 3 together, and given the 11.63% correlation between CIV and OIV, my finding indicates that CIV in CDS market fairly matches the volatility situation in stock option market, furthermore, there is some information in option market that is not reflected in CDS market, and vice versa, which allows the two variables to be mutually complementary. This finding is robust to the inclusion of controlling variables such as the option Delta, open interest and maturity.

4.2 Forecast stock realized volatility with CIV

The predictability of OIV on future realized volatility has been identified extensively, for instance, Christensen and Prabhala (1998) find the implied volatility by S&P 100 index option outperforms and even subsumes past volatility in forecasting future volatility; Cao, Yu and Zhong (2010) show that the implied volatility of corporate equity option forecast future realized volatility more efficiently than historical volatility.

In this section I investigate the predictability of CIV on future realized volatility. My argument is if OIV is an efficient forecast, CIV may add its contribution since it is related and complementary to OIV. The regression is

$$FRV_{i,t} = \alpha_i + \beta_{\mathrm{i}}^{\mathrm{his}} \times HRV_{i,t} + \beta_i^{CV} \times CV_{i,t} + \varepsilon_{i,t}, i = [1, 2, ...N] \tag{9}$$

where $FRV_{i,t}$ and $HRV_{i,t}$ are the future and historical realized volatility for firm i at t, $CV_{i,t}$ is the controlling variable that can be either $CIV_{i,t}$ or $OIV_{i,t}$ or both. I use simple standard deviation of future and previous one-year stock returns to estimate the $FRV_{i,t}$ and $HRV_{i,t}$ at each t. Data is again from the CRSP.

Table 4 reports the regression results for three tests that regressing future realized volatility on historical volatility, CIV and OIV, on historical volatility and CIV, and on historical volatility and OIV. Such test design shows clearly the possible contribution of adding a CIV variable. Several important observations arise. First, consistent with other studies, I find implied volatility is a strong forecast of future realized volatility. The coefficient estimate for OIV is positively significant at the 1% level, signifying the forward-looking nature of OIV. The magnitude of OIV estimate is larger than that of historical volatility, indicating the outperformance of OIV.

Second, CIV outperforms OIV in forecasting the future realized volatility. When regressing on both CIV and historical volatility, the coefficient estimate for CIV is positively significant at the 1% level. Again the magnitude of historical volatility is smaller than that of CIV. The adjusted R^2 increases to 20.90%, from 18.32% for the test on OIV and historical volatility, for the whole sample, and from 13.21% to 19.33% and from 20.29% to 21.51% for the investment- and junk-grade group, respectively. In addition, the constant term becomes insignificant any more. When regressing on CIV, OIV and historical volatility, CIV has the largest coefficient estimate. The adjusted R^2 is further increased to 30.00%, 25.17% and 31.86% for the whole sample, the investment- and junk-grade group.

Third, the future realized volatilities of the junk-grade firms seem to be easier predicted than those of the investment-grade firms, regardless of the test variables. This could be due to the fact that both CDS and out-of-money put option are protecting the firm default risk, which is, obviously, more imperative for junk-grade firms, consequently, CDS and put option markets contain more timely and accurate information for those firms.

Fourth, the impact of historical volatility on future volatility is negative, consistent with stock volatility's mean-reverting characteristics found in Merville and Pieptea (1989) and many others.

Overall I find CIV is an effective forecast of underlying stock future volatility, beyond the roles of OIV and historical volatility. The predictability of credit spread has been examined recently by several researchers (Han and Zhou, 2011, Faust, et al., 2013, and Friewald, Wagner and Zechner, 2014). Different from their tests on the first moment (economic indicator or equity premium), this study examines the CDS predictability on the second moment, the variation of stock market, thus it can be viewed as a complement to their work.

4.3 Trading strategy based on cross-market information

Mean reversion strategy refers to a trading activity that assumes both an asset's high and low prices are temporary, its price tends to move to the average level over time, therefore an investor buys an asset when its price is at a relatively low level, and sells it when its price is at a high level. Similarly a cross-market mean reversion trading involves the long of relatively underpriced asset and the short of overpriced asset.

CIV and OIV are highly related, if there exists a liner combination of the two series that is stationary, or co-integrated, we can build a cross-market mean reversion trading strategy. I run a regression as follows

$$CIV_{i,t} = \beta_i \times OIV_{i,t} + \varepsilon_{i,t}, i = [1, 2, ...N] \tag{10}$$

and test the stationarity of the CIVOIV spread term $\varepsilon_{i,t}$. CIV and OIV are co-integrated if the spread is stationary. A standard ADF (Augmented DickeyFuller) is conducted on $\varepsilon_{i,t}$ for each firm i. Over the periods from January 2001 to December 2011, 332 out of 363 firms (91.71%) are shown to have stationary CIVOIV spreads.

I then design a trading strategy following Balvers, Wu and Gilliland (2000). On each observation t0, I first calculate the CIVOIV spreads series $\varepsilon_{i,t}$, t=1,...,t0 using all previous data up to t0 and standardize the spreads as $\frac{\varepsilon_{i,t}-\mu_i}{\sigma_i}$ called z-score, where μ_i and σ_i is the average and standard deviation of $\varepsilon_{i,t}$. I then divide all CDSs into four Quartiles based on the values of z-scores at t0. The first Quartile group consists of CDSs with the lowest z-scores and is deemed as the most underpriced; the fourth Quartile group consists of CDSs with the highest z-scores and is the most overpriced. I long the CDSs in the first Quartile and short the fourth Quartile till one week later at t0+1, when I re-calculate all z-scores and adjust my portfolio if necessary.

I choose to trade CDS rather than put option because CDS has a constant 5-year maturity so there is no time decay effect involved in the strategy. I set t0 at one-third of the sample (April, 2005) and implement this strategy till the end of sample (December, 2011). CDS return is calculated as the log of st over st-1, in order to estimate the return, I exclude those

CDSs with no available quote at t-1. The return of a Quartile group is the equally weighted return of all CDSs in the group, and no transaction cost is imposed.

Figure 1 plots the cumulative returns of the long-short strategy, compared with the benchmark buy-and-hold strategy. Although the final cumulative returns are similar, the long-short strategy generates much more stable incomes and its performance is not impact by the financial crisis, unlike that of the buy-and-hold strategy suffering a large drawdown from 2009 to 2010. Figure 1 also plots the returns of the four Quartile groups: clearly the first and second Quartile groups perform much better than the third and fourth Quartile.

Table 5 shows the trading performance statistics. Maximum drawdown is an indicator of the risk of a strategy. It measures the largest single drop from the highest to the lowest in the value of cumulative returns. Sharpe ratio measures the risk adjusted performance and is calculated by subtracting the risk-free rate and dividing the standard deviation. A larger Sharpe ratio and a lower Maximum drawdown signal a better trading performance. The long-short strategy earns an annualized return at 17.31%, beating the 8.96% return generated by the buy-and-hold strategy. More importantly, the long-short strategy has a much smaller maximum drawdown at 14.19% and standardized deviation at 8.56%, yielding a great Sharpe ratio at 1.7188, while the Sharpe ratio is only 0.1790, 0.5397, 0.5415, -0.0606, and -0.3164 for the buy-and-hold strategy, first, second, third and fourth Quartile group, respectively.

4.4 Discussion: The reasons of CIV's good performance

CIV is mutually complementary to OIV, it has good performance in explaining OIV, forecasting future volatility, and triggering profitable trading strategy. Readers may be curious about the mechanism. In this section I offer two possible reasons. First, CIV and OIV are complementary because they capture different volatility patterns. CIV is more persistent than OIV, as reported in Table 1, the averaged standard deviation of CIV is only 10.88%, while that of OIV is doubled at 20.11%. Figure 2 plots the time series of the averaged CIV and OIV series across firms. Generally CIV and OIV share similar up and down patterns, nevertheless, CIV is more stable and persistent. Christoffersen, et al., (2008) propose a model for option pricing in which the volatility consists of two components. One is a long-run persistent component and the other is a short-run volatile component. Their model has a superior performance than a single-component volatility model. Therefore one possible reason of CIV's good performance is it represents the long-run trend, complementary to the relatively short-run OIV.

Second, the reason that both CIV and OIV have strong predictability on stock volatility is the price discovery process among CDS, stock and option markets. Numerous studies have been done on the lead-lag relation across markets (Acharya and Johnson, 2007; Berndt and Ostrovnaya, 2008; Cao, Yu and Zhong, 2010, Carr and Wu, 2010). A general finding is that both option and credit markets lead equity market, therefore the information from both option and credit market contains useful message for the future movement deviation of equity market. My findings in this study from a different perspective provide additional evidence. However, the lead-lag relation between option and credit markets is mixed, my trading strategy performance on the CDS market suggests that it seems option dominates credit market, so those relatively under- and over-priced CDS contracts with respect to their associated option contracts tends to revert hereafter.

5 Conclusion

Both CDS and out-of-money put option protect investor against downside risk, many investigations have been undertaken to understand the relation between these two assets. Different from previous studies, this paper develops a direct linkage by inferring underlying asset volatility from CDS spreads. Applying the method on weekly US corporate CDS from January 2001 to December 2011, I find the inferred stock volatility provides very useful information on both option and equity market. The inferred volatility from CDS and the implied volatility from out-of-money option market are mutually complementary. CDS inferred volatility dominates option implied volatility in forecasting stock future realized volatility. A trading strategy based on the indispensable relation between CDS and option market generates a great risk-adjusted return. The findings of this paper contribute to the literature on cross disciplinary research among CDS, option and equity markets.

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Table 1: Summary statistics

Variable	Mean	S.D.	Min	0.25	Median	0.75	Max	Total
# of firms								363
# of weeks								514
# of observations	253	129	52	143	240	348	514	
Maturity (day)	286	238	3	94	199	465	969	
E (millions)	2987.81	4764.06	156.94	640.55	1427.82	3000.71	52578.56	
D (millions)	1224.20	5812.78	0.02	84.21	194.28	474.34	72024.91	
r (%)	2.11	1.67	0.09	0.47	1.75	3.37	5.30	
s	1.45	2.23	0.02	0.37	0.70	1.58	50.47	
CIV (%)	42.51	10.88	3.32	36.33	41.64	47.63	146.17	
OIV (%)	44.72	20.11	8.63	31.42	39.73	51.90	284.46	
cor(s, CIV)	26.30	40.81	-83.76	-3.97	31.17	56.67	98.73	
cor(CIV, OIV)	11.63	36.92	-79.01	-15.60	12.70	40.15	92.75	

This table reports the summary statistics of data. "# of firms" is the total number of firms in sample, "# of weeks" is the total number of weeks, "# of observations" is the number of observations for each firm, Maturity is the put option maturity, E is the market equity value, D is the debt value, r is the risk-free rate, s is the CDS spread, CIV is the CDS inferred volatility, OIV is the option implied volatility, cor(s, CIV) is the sample correlation between CDS spreads and CIV, and cor(CIV, OIV) is the sample correlation between CIV and OIV for each firm.

Table 2: Regression results of OIV on CIV.

	Estimate	t-statistics	p-value	Estimate	t-statistics	p-value	N
Panel A: Investment grade							
Constant	0.2171***	3.3744	0.0011	0.3078***	4.8366	0.0000	101
CIV	0.4973***	2.8931	0.0047	0.4728***	2.7518	0.0070	
Delta				0.6553***	16.5655	0.0000	
OI				-0.0000*	-1.7161	0.0892	
Maturity				-0.0000***	-3.0036	0.0034	
Adj R^2	0.1276			0.1959			
Panel B: Junk grade							
Constant	0.1480***	2.7209	0.0069	0.2299***	4.2663	0.0000	262
CIV	0.9849***	6.3626	0.0000	0.9764***	6.4231	0.0000	
Delta				0.7229***	16.9282	0.0000	
OI				0.0000	1.0046	0.3160	
Maturity				-0.0000***	-3.8347	0.0002	
Adj R^2	0.1512			0.2223			
Panel C: Whole							
Constant	0.1672***	3.8769	0.0001	0.2516***	5.8876	0.0000	363
CIV	0.8492***	6.9637	0.0000	0.8363***	6.9605	0.0000	
Delta				0.7041***	21.5069	0.0000	
OI				0.0000	-0.1185	0.9057	
Maturity				-0.0000***	-4.7889	0.0000	
Adj R^2	0.1446			0.2150			

This table reports the regression results of OIV on CIV, controlling for other variables such as the option Delta, OI (open interest), and Maturity. Adjusted R2 is shown for each regression. Panel A, B, and C is for the test when only the investment-grade firms, only the junk-grade firms and the whole sample firms are used, respectively. N is the number of firms. ***, **, and * denotes the significance level at 1%, 5% and 10%, respectively.

Table 3: Regression results of CIV on OIV.

	Estimate	t-statistics	p-value	Estimate	t-statistics	p-value	N
Panel A: Investment grade							
Constant	0.4142***	25.9379	0.0000	0.4085***	24.1477	0.0000	101
OIV	0.0790***	3.1455	0.0022	0.0781***	3.0525	0.0029	
Delta				-0.0167	-0.7892	0.4319	
OI				0.0000***	2.8526	0.0053	
Maturity				0.0000***	3.138	0.0022	
Adj R^2	0.1276			0.1702			
Panel B: Junk grade							
Constant	0.4089***	55.9756	0.0000	0.4052***	49.6562	0.0000	262
OIV	0.0217**	2.3336	0.0204	0.0237**	2.5302	0.012	
Delta				0.0053	0.4727	0.6368	
OI				0.0000*	1.7061	0.0892	
Maturity				0.0000***	3.1035	0.0021	
Adj R^2	0.1512			0.1965			
Panel C: Whole							
Constant	0.4104***	59.6178	0.0000	0.4061***	53.9566	0.0000	363
OIV	0.0377***	3.8559	0.0001	0.0389***	3.9307	0.0001	
Delta				-0.0009	-0.0853	0.9321	
OI				0.0000***	3.266	0.0012	
Maturity				0.0000***	4.3641	0.0000	
Adj R^2	0.1446			0.1892			

This table reports the regression results of CIV on OIV, controlling for other variables such as the option Delta, OI (open interest), and Maturity. Adjusted R2 is shown for each regression. Panel A, B, and C is for the test when only the investment-grade firms, only the junk-grade firms and the whole sample firms are used, respectively. N is the number of firms. ***, **, and * denotes the significance level at 1%, 5% and 10%, respectively.

Table 4: Forecast future realized volatility with CIV.

	Estimate	t-statistics	p-value	N	Estimate	t-statistics	p-value	Estimate	t-statistics	p-value
Panel A: Investment grade										
Constant	0.0327	0.5726	0.5682	101	0.0664	1.1252	0.2632	0.2054***	25.1508	0.0000
CIV	0.4877***	3.038	0.0030		0.5049***	3.0516	0.0029			
OIV	0.2385***	11.1953	0.0000					0.3050***	15.4255	0.0000
His.vol	-0.0884***	-3.3403	0.0012		0.0936***	2.6551	0.0092	-0.0872***	-3.8257	0.0002
Adj R^2	0.2517				0.1933			0.1321		
Panel B: Junk grade										
Constant	-0.0797	-1.4931	0.1366	262	-0.1068*	-1.779	0.0764	0.2509***	22.0400	0.0000
CIV	0.9800***	6.7074	0.0000		1.3309***	8.0396	0.0000			
OIV	0.4066***	16.863	0.0000					0.4822***	20.7413	0.0000
His.vol	-0.1661***	-4.2984	0.0000		0.0975***	3.2571	0.0013	-0.1687***	-4.6763	0.0000
Adj R^2	0.3186				0.2151			0.2029		
Panel C: Whole										
Constant	-0.0484	-1.1597	0.2469	363	-0.0585	-1.2589	0.2089	0.2382***	27.7633	0.0000
CIV	0.8426***	7.3309	0.0000		1.1004***	8.5088	0.0000			
OIV	0.3597***	19.1527	0.0000					0.4328***	23.8818	0.0000
His.vol	-0.1444***	-5.0039	0.0000		0.0964***	4.0691	0.0001	-0.1460***	-5.4412	0.0000
Adj R^2	0.3000				0.2090			0.1832		

This table reports the regression results of future realized volatility on historical volatility (His.vol) and CIV and /or CIV. Adjusted R2 is shown for each regression. Panel A, B, and C is for the test when only the investment-grade firms, only the junk-grade firms and the whole sample firms are used, respectively. N is the number of firms. ***, **, and * denotes the significance level at 1%, 5% and 10%, respectively.

Table 5: Trading strategy performance

	Annualized	**Cumulative**	**Sharpe ratio**	**S.D.**	**Max Drawdown**
Buy-and-Hold	0.0896	1.0012	0.1790	0.3656	0.7084
First Quartile	0.2406	1.9320	0.5397	0.3949	0.7355
Second Quartile	0.2393	1.9149	0.5415	0.3911	0.7049
Third Quartile	-0.0006	0.4572	-0.0606	0.3767	0.7424
Fourth Quartile	-0.0923	-0.2260	-0.3164	0.3556	0.7147
Long-short	0.1731	1.0790	1.7188	0.0856	0.1419

This table reports the trading performance for each Quartile group and for a long-short strategy, compared with that for a buy-and-hold strategy. Trading starts from April 2005 to December 2011, without accounting for transaction costs.

Figure 1. Cumulative returns of trading strategy.
Plots of the cumulative returns of the long-short trading strategy (in blue), compared with the returns of the buy-and-hold benchmark strategy (in green). The returns for the four Quartile groups are shown as illustration. Trading starts from from April 2005 to December 2011, without accounting for transaction costs.

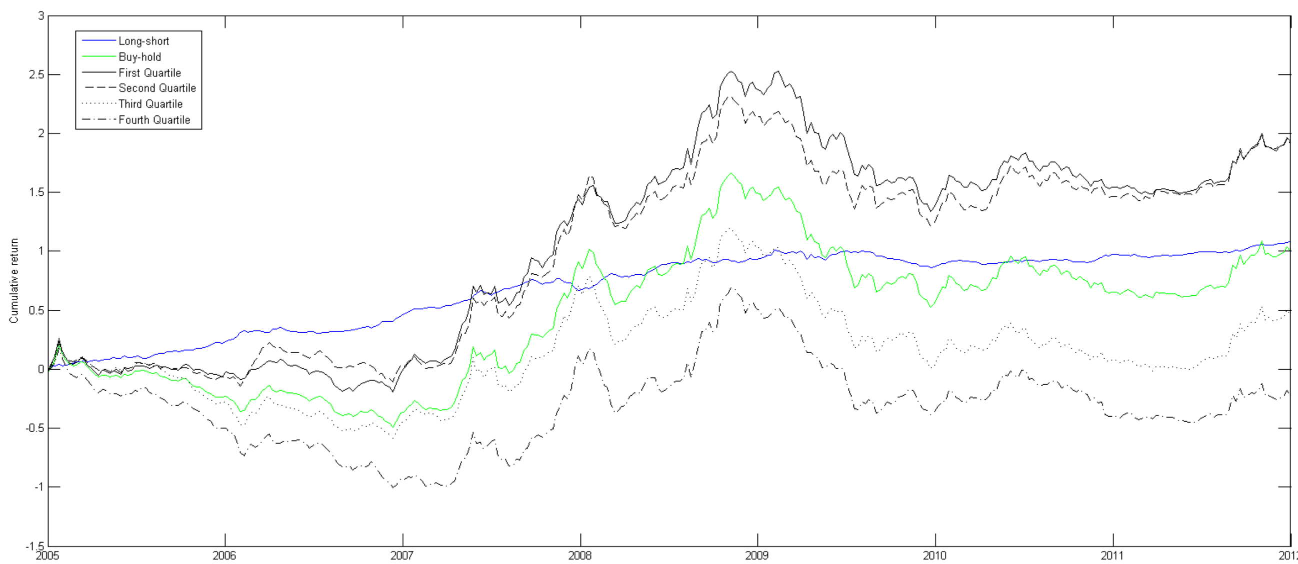

Figure 2. Time series plots of CIV and OIV.
Left y-axis is for CIV, and right y-axis is for OIV.