The information content of CDS implied volatility and associated trading strategies

Abstract

Using the theoretical link between put options and credit default swaps (CDS) in a very general setting, we develop a robust measure of CDS implied volatility (CIV) that captures the information content of CDS markets. Specifically, we use the unit recovery claim to bridge CDS and deep out-of-the-money put options of the same firm and then back out CIV via the binomial tree. Our CIV measure strongly co-moves with the option implied volatility (OIV), with a correlation coefficient of 0.8. Based on the standardized difference between CIV and OIV, we construct CDS and option trading strategies. Without taking transaction costs into account, the long-short CDS trading strategy achieves an annualized return of 58.29% and a Sharpe ratio of 2.97, which can not be explained by non-parametric skewness and volatility risk.

Keywords: CDS, Implied volatility, Default probability, Unit recovery claim, Trading strategies

JEL classification: C13, C51, G11, G12.

1. Introduction

Credit default swaps (CDS hereafter) contain important information about their referencing entities. Studies of the information content of CDS have directly focus on CDS spreads (Lee et al., 2018). However, theories explaining the links between CDS spreads and other marketable instruments suggest that these relationships are mostly nonlinear (Friewald et al., 2014). It is, therefore, useful to present the information content of CDS spreads in a information measure that is compatible with other information-rich instruments, preferably dimensionless information. An ideal candidate for such a measure is implied volatility.

Despite its obvious importance, the fast-growing CDS market has not spurred the development of a widely accepted measure of CDS implied volatility (CIV). To fill this gap, we use the unit recovery claim (URC) proposed by Carr & Wu (2011) to bridge CDS and deep out-of-the-money (OTM) put options of the same company and then back out CIV via the binomial tree. The URC refers to a fundamental claim that has a fixed expiration date and pays 1 dollar when a default event occurs before its maturity, and 0 otherwise. Carr & Wu (2011) show that American put option prices, especially deep OTM puts, are highly correlated with CDS spreads due to the URC embedded in these instruments.

We argue that our measure of CIV is better than the existing measures, not only because we use the American type of options instead of the European ones, but also due to the fewer assumptions that we make. i) To the best of our knowledge, the first attempt to construct a CIV measure is Guo (2016), who equates the conditional default probability in CDS valuation with the 5-year default probability within the framework of Merton's structural distance to default (DD) model (Merton, 1974). ii) The other related work is Kelly et al. (2019), which also relies on the structural DD model, but makes an alternative approximation that *"equates the value of the put option implicit in firms' debt to the capitalized value of future CDS spread payment."*

Despite its popularity, it is well-known that Merton's structural DD model produces an insufficient statistic for the default probability, which is only weakly correlated with the CDS default probability after conditioning on other variables (Bharath & Shumway, 2008; Campbell et al., 2008). Following this strand of literature, we build our measure of CIV via the reduced-form model of Carr & Wu (2011) rather than the structural DD model of Merton (1974).

We evaluate our measure of CIV against the measures in Guo (2016) and Kelly et al. (2019) in several ways. First, we check the correlation coefficient between each CIV measure and the CDS spread of the same company. When the default risk increases for a firm, widening its credit spread, a good measure of CIV should be capable of capturing this and thus be strongly correlated with the CDS spread.

Second, we check the co-movements between the CIV measures and option implied volatility (OIV hereafter). The price of deep out-of-the-money (OTM hereafter) put options are mainly driven by the default probability of the company, similar to credit insurance contracts. The URC of a company can be constructed using either the American put options underlying its equity or the CDS spreads referencing its debt. Other things being equal, we conjecture that a good measure of CIV should be strongly correlated with OIV, and that this correction will decrease with the maturity difference between the options and CDS of the same company.

Third, we implement time-series regressions of OIV on each CIV measure for each company, and of each CIV measure on OIV, controlling for the most relevant variables such as option delta, open interest, and maturity. We do this not only for the full sample, but also for subsamples, especially for subsamples of companies with investment-grade ratings (BBB and above credit rating), and junk-grade ratings (BB and below credit rating), as they are the most likely to default.

Fourth, as Carr & Wu (2011) argue that the estimated URC from CDS and American puts co-mmove and tend to converge later, we examine whether there exists a co-integration relationship between CIV and OIV, and then build a zero-cost long-short trading strategy by sorting CDS on the CIV-OIV spread Z-score, following Balvers et al. (2000). Specifically, we sort the CDS into five quintiles based on the CIV-OIV spread Z-score, and long the quintile of CDS that have the smallest Z-scores and short the quintile of CDS that have the largest Z-scores (and rebalance whenever necessary). We test the portfolio trading performance (e.g., profitability) under this specification with three measures of CIV. Other things being equal, we speculate that a better measure of CIV should be associated with a better-performing trading strategy.

Two interesting findings emerge when we apply our measure to a sample of weekly U.S. corporate CDS and OTM put options from our 2002-2014 sample period.

On the one hand, we demonstrate that our CIV measure is more correlated with the CDS spread than either of the CIV measures from Guo (2016) or Kelly et al. (2019). Specifically, our CIV measure is much more strongly correlated (with a correlation coefficient of 0.8) with the OIV than either of the CIV measures from Guo (2016) or Kelly et al. (2019), and this correction decreases with the maturity difference between options and CDS of the same company. The value of our CIV measure decreases with the moneyness of tradable put options, whereas the counterparts from Guo (2016) and Kelly et al. (2019) depend on the moneyness (leverage) of options. Compared to the CIV measures from Guo (2016) and Kelly et al. (2019), our CIV measure has a larger explanatory power for OIV, and can be better explained by OIV in both the full sample and subsamples. According to a simple univariate regression of OIV on CIV with an intercept, our CIV measure significantly explains 66.38% (adjusted R^2) of the variation of OIV in the full sample, whereas the CIV measures from Guo (2016) and Kelly et al. (2019) can only explain 14.46% and 24.10%, respectively. The estimated coefficient of our CIV measure is 1.0362 for the full sample, whereas its counterparts in Guo (2016) and Kelly et al. (2019) are 0.8492 and 0.7729, respectively. We obtain similar values when we use OIV to explain the three measures of CIV. Those findings are robust to controlling for other option characteristics such as delta, open interest (OI), and maturity.

On the other hand, we identify a co-integration relationship between our CIV measure and OIV in 85% of the cases in our sample. Based on the standardized difference between CIV and OIV, we construct CDS and option trading strategies. Without taking transaction costs into account, the long-short CDS trading strategy achieves an annualized return of 58.29% and a Sharpe ratio of 2.97 for our 5-year CIV measure, which can not be explained by non-parametric skewness and volatility risk. The profitability of this trading strategy is higher if we use our 1-year CIV measure, and to a lesser extent holds for our CIV measure at other maturities. The profitability of this trading strategy decreases when we replace our CIV measure with the one either from Guo (2016) or from Kelly et al. (2019). Hence, we construct a similar option trading strategy. We identify profitability for the deep OTM puts and deep OTM delta-hedging, but not for the at-the-money (ATM hereafter) straddle and ATM call delta-hedging, which suggests that CIV has a strong cointegration relationship with the OTM-OIV but not with the ATM-OIV, and provides additional support for Carr & Wu (2011) who emphasize the link between CDS and deep OTM American puts only. For our CIV measure at all maturity lengthens, we identify a smirk curve when we plot CIV against the moneyness of tradable options.

This paper makes at least four contributions. First, we are the first to use the URC proposed by Carr & Wu (2011) to bridge CDS and deep OTM put options of the same company, and then back out CIV via the binomial tree. The practical application of URC is limited, and our CIV measure reveals the uncovered side of URC.

Second, we extend Carr & Wu (2011) and derive the theoretical relationship between CDS and American put options in a very general setting, decomposing American options into a down-and-out barrier option, a URC, and an early exercise premium. This decomposition is not only useful in guiding our empirical approach, but it also brings insights into the differences in the information content of CDS and American put options.

Third, we compare our CIV measure with the two existing CIV measures. We demonstrate that our measure outperforms the existing measures in almost every aspect of the above and hence provides a useful tool for future researchers in this area.

Finally, based on our 5-year CIV measure, we propose a zero-cost long-short CDS trading strategy that achieves a gross annualized return of 58.29% and a Sharpe ratio of 2.97, which can not be explained by non-parametric skewness and volatility risk. The profitability of this strategy underscores its importance, especially for practitioners.

Our study differs from most studies of the CDS and options markets in at least two ways. On the one hand, we focus on deep OTM put options, while most studies focus on the ATM options (Goyal & Saretto, 2009; Yan, 2011; Cremers et al., 2015). On the other hand, most studies price the derivatives based on their underlying assets, whereas this paper follows a few very recent papers and presents a joint framework for derivatives only (Cao et al., 2010; Carr & Wu, 2011).

The remainder of this paper is organized as follows. Section 2 provides a brief review of the methodology. Section 3 describes the data and screening criteria. Based on the results of the regressions and option portfolio strategies, Section 4 presents the results, robustness checks, and the potential reasons for the excess return associated with our trading strategy. Section 5 concludes.

2. Estimating CDS implied equity volatility

Carr & Wu (2011) identify a robust link between CDS and American put options through URC. The URC is an Arrow & Debreu (1954) security with a fixed maturity T. It will pay one dollar at the default time τ when $\tau \leq T$, and zero otherwise.

Denote $URC(t,T)$ as the value of the URC at time t, the interest rate as r, and the default arrival rate as λ. The value of URC at time t is

$$URC(t,T) = \mathbb{E}_t^{\mathbb{Q}}\left[e^{-r\tau}1(\tau < T)\right] = \int_t^T \lambda e^{-(r+\lambda)s} ds = \lambda \frac{1 - e^{-(r+\lambda)(T-t)}}{r+\lambda} \quad (1)$$

The risk-neutral default probability[1] over the same period can be shown as

$$\mathbb{D}(t,T) = \mathbb{E}_t^{\mathbb{Q}}[1(\tau < T)] = 1 - e^{-\lambda(T-t)} \tag{2}$$

Comparing Equations (1) and (2), we find that the present value of the URC is lower than the risk-neutral probability, and that the forward price of the URC is higher than the risk-neutral probability, due to different payment times:

$$URC(t,T) \leq \mathbb{D}(t,T) \leq e^{r(T-t)} URC(t,T), \quad r \geq 0 \tag{3}$$

Carr & Wu (2011) show the existence of a default corridor [A, B] that a stock price may never enter. If there is no default, the stock price will always be above B, whereas after default the upper bound of the stock price is A. If the strike price K of an American put option falls into the default corridor, the put option will be out of money and will never be exercised if there is no default and in the money if a default happens. Carr & Wu (2011) further prove that if a default happens, the optimal behavior of the option holder is to exercise it immediately at the default time τ. We then can construct a portfolio with two American put options where their strike prices K_1 and $K_2 (K_1 < K_2)$ both fall into the default corridor. We long $1/(K_2 - K_1)$ of a unit of the K_2 put and short the same amount of the K_1 put. If there is no default before expiration, the payoff of the portfolio is zero. If the firm defaults before or at the expiration date, the option holder will exercise the option immediately, and the payoff is $(K_2 - K_1)/(K_2 - K_1)$, which is one dollar. The option portfolio will have the same payoff as a URC contract of the same company with the same maturity T. Assuming that there are no risk-free arbitrage opportunities, the URC and the American put options should have the same price. Therefore, the URC can be constructed using the deep OTM American put options. Therefore, the value

[1] This risk-neutral probability is the forward price of another Arrow & Debreu (1954) security paying off one dollar at maturity T if. $\tau \leq T$, and zero otherwise.

of $URC^{\text{ American-put }}$ is given by

$$URC^{\text{ American-put }} = \frac{P_1 - P_2}{K_1 - K_2} \tag{4}$$

where [A $\leq K_2, K_1 \leq B$] are set as the default corridor so that before the default occurs, the stock price randomly walks above the corridor. However, the price corridor is totally inaccessible prior to the default. Following Carr & Wu (2011), we, therefore, make a simple assumption that K_2 equals to 0 upon default; then the URC can be simplified as

$$URC^{\text{ American-put }} = \frac{P_1}{K_1} \tag{5}$$

The most actively traded credit contracts are CDS that references corporate bonds. A CDS contract helps trading parties to carry out risk conversions on a designated credit event within a certain period. The buyer of the CDS contract pays a fixed premium to the seller before the occurrence of the credit event. Once the prespecified credit event occurs, the CDS contract protects the buyer against paying a premium, and the seller pays the par value in return for the corporate bond. Denoting S as the T-year CDS spread and R as a known recovery rate, the URC can be constructed using the CDS spread as

$$URC^{\text{CDS}} = \frac{S}{1-R} \frac{1 - e^{-\left(r + \frac{S}{1-R}\right)T}}{r + \frac{S}{1-R}} \tag{6}$$

We assume that $URC^{\text{CDS}} = URC^{\text{ American-put }}$ to invert the American put option price to obtain CDS-inferred implied volatility (σ_{CIV}) by applying the binomial tree pricing method with 200 steps.

$$P_1^* = K_1 URC^{\text{CDS}} = P\left(S_t, K_1, T, r, \sigma_{CIV}\right) \tag{7}$$

where P_1^* denotes the American put option constructed using the CDS spread with a strike price K_1, P is the observed equity American put option with the same strike price K_1, and σ_{CIV} is the corresponding implied volatility. We use r to denote the risk-free rate related to a deterministic function of time.

Equation (7) relies crucially on two assumptions. First, the interest rate and the default arrival rate are assumed to be constant across time, and therefore, the term structure of the CDS spread is flat. We, therefore, infer the price of the URC across all of the maturities, using the CDS spread of any maturity. Second, there exists a default corridor $[A, B]$ that the stock price can never enter. Third, the strike price of the put option K_1 is assumed to fall within the default corridor, more specifically, $K_1 < B$; together with the second assumption, this means the price of a put option with strike K_1 can be expressed as the product of the URC and the strike price. The first two assumptions are reasonably supported by empirical evidence and unlikely to cause any issue in our empirical work. The third assumption, however, is more problematic and warrants further discussion.

For a small firm with unstable cash reserves and capital structure, one may safely assume that there exists a deep OTM put option with a strike price that falls below the upper bound of the default barrier. The same argument does not apply to a more established firm with no foreseeable credit-related issues; the lowest strike price on its put option chain may be well above a hypothetical default corridor. Ex-post analysis of all of the default cases between 2000 and 2017 also shows that firms that defaulted on their debt obligation often had OTM put strike prices above the actual jump to default prices one year prior to the default event. In Appendix A, we derive a theoretical link between the CDS and OTM put outside of the default corridor.

3. Data and descriptive statistics

We analyze the company-level data in a sample of USD-denominated CDS for every Wednesday from January 1, 2002, to December 31, 2014. The CDS data are provided by the Markit database. To obtain reliable and less mismatched data for data calibration, we apply two screening criteria. First, the corporate CDS should contain at least 1 year of trading data, which means at least 52 weeks of observations. Second, the CDS must have a modified restructuring clause, with an unchanged recovery rate, resulting in a smaller pricing error. The risk-free rates are the constant maturity rates of 1-, 3-, 5-, 7-, 10-year Treasury bonds which are extracted from the Federal Reserve Board. The equity options data are obtained from the Option Metrics via Wharton Research Data Services (WRDS). The way for connecting American put options and CDS are as follows. (1) bid quotes of options must be greater than 0. (2) the time to maturity is more than 360 days to minimize maturity mismatch. (3) the delta of the corporate options must be greater than -0.15. (4) finally, the options with the highest daily OI are selected. If there are more than two options after applying the above criteria, we use the American put with the delta closest to 0. Our filtering criteria for equity, CDS, and options are consistent with Carr & Wu (2011).

Our final sample is made up of 120,588 pairs of CIV and OIV. We further remove any observations with extreme equity or debt values (bottom and top 1%), and the final sample covers 335 firms across 666 weeks. The descriptive statistics of the key variables for 5-year CDS are shown in Table 1. On average, each firm has 360 weeks of CIV and OIV pairs, and the observations range from 52 to 666 weeks. The maturity of put options spans 360 to 969 days with an average of 546 days, indicating that most of the options have a maturity of between 1 and 2 years. The mean value of OIV is higher than the one of CIV for about 8.5% of the pairs with similar standard deviations. The average correlation between CIV and OIV is very high (79.98%), and the correlation between CDS spreads (s) and CIV is 77.87% on average. The standard deviations of the correlations are lower than 20%. The high and stable correlation between CIV and OIV indicates that they may be complementary.

[Insert Table 1 about here]

Carr & Wu (2011) suggest that the link between CDS and American puts would be stronger for deep OTM options. Therefore, we examine how option moneyness and CDS maturity affect CDS and OIV in Table 1, Panel B. For all of the CDS maturities, the CIV of CDS with low moneyness (0%-50%) is higher than the ones with high moneyness (50%-100%), and are closer to OIV, indicating that the CDS-put option link is stronger when moneyness is low. Across different CDS terms, the CIV estimation is generally higher for short (1 year, i.e., CIV-1) and long (7 and 10 years, i.e., CIV-7 and CIV-10, respectively) maturities, and relatively lower for medium-term CDS (3 or 5 years). The mean correlation between CIV and OIV is highest for CIV-1 (0.899) and declines with CDS maturity.[2] This is consistent with the low level of maturity mismatch between 1-year CDS and American put options. The closest difference between CIV and OIV (0.584 and 0.600) is found in 1-year CDS with low moneyness. The very small difference also supports the argument of Carr & Wu (2011) that CDS can be valued using the deepest OTM American put options. Figure 1 provides the scatter between URCs replicated by American put and CDS.

[Insert fig. 1 about here]

[Insert figs. 2 to 4 about here]

We estimate the CIV measure from Kelly et al. (2019) in Panel C. This measure has a much lower mean correlation with OIV and CDS spread (31.14% and 47.19%, respectively) than our measure, and the standard deviations of the correlations are very high compared to the mean. In addition, the measure of CIV from Guo (2016) has even lower correlations with OIV and CDS spread and even higher correlation volatility (See Table 1 in Guo (2016)).

We further plot the time series of the average OIV and the three different measures of CIV in Figure 2 (our measure), Figure 3 (Kelly et al., 2019), and Figure 4 (Guo, 2016), respectively. Figure 2 shows that mean CIV are always lower than OIV. The CIV reflects the downside volatility. Thus, CIVs are

[2]The estimation method for the mean correlation is different in Panel B than in Panels A and C. In Panels A and C, we only have one CIV and OIV pair for each firm. We then calculate the correlation between each firm and take the average. In Panel B, we have many CIV-OIV pairs for one firm, so we calculate the average correlation of all of the CIV-OIV pairs.

intuitively lower than OIV. However, CIV from structural models (Guo, 2016; Kelly et al., 2019) do not have this property. Our measure demonstrates a very similar pattern to OIV, whereas the other measures, which are based on structural models, are less volatile than OIV. Compared with these two CIV measures, our measure shows a significantly high and stable correlation between OIV and CDS spread, and is perhaps a better measure of the link between CDS and options markets.

[Insert Figure 5 about here]

Figure 5 plots the scatter of weekly CIV versus moneyness for different maturities. In general, the volatility derived from CDS illustrates a clear smirk pattern for the option moneyness. The CIVs with different maturities tend to decrease with the moneyness monotonically. However, the curve is slightly upward-sloping at the ending point, because of the large volume of outliers in high moneyness variable. It is worth emphasizing that the 1-year CIV smirk is steepest, which is similar to the pattern of OIV. As the CIV maturity increases, the scatter plot shows a flat trend, and the data distribution becomes more centralized.

4. Empirical results

4.1. Relationship between CIV and OIV

To further examine the strong correlation between CIV and OIV, we run a series of regressions. First, we examine whether CIV can explain OIV:

$$OIV_{i,t} = \alpha_i + \beta_i CIV_{i,t} + \beta_i^{CV} \text{ ControlVariables }_{i,t} + \varepsilon_{i,t} \tag{8}$$

where the control variables include the delta of the option, OI, and maturity. We strictly follow the literature (i.e., Guo (2016)) to make our choice of control variables. The results are shown in Table 2. The three panels are for categories of firms: investment-grade firms, junk-grade firms, and the full sample of firms.

[Insert Table 2 about here]

The coefficient estimators for CIV are 1.443 (investment-grade), 1.161 (junk-grade), and 1.231 (full sample), which are all greater than one. Thus, CIV can explain the variation in OIV, which is positive and statistically significant at the 1% level. The Adjusted R^2 is 66.38% when the full sample is used. With respect to predicting the performance of OIV, CIV contains a little more information on investment-level firms than on junk-level firms, with an Adjusted R^2 of 66.72% versus 66.26%. The constant term α_i significantly explains OIV at the 1% level as well, which hints that some of the information contained in OIV is not captured by CIV.

[Insert Table 3 about here]

We redo the same exercise in Table 3 but change the dependent variable to CIV,

$$CIV_{i,t} = \alpha_i + \beta_i OIV_{i,t} + \beta_i^{CV} \text{ ControlVariables }_{i,t} + \varepsilon_{i,t} \tag{9}$$

The results of regressing CIV on OIV shows that the estimated coefficients for OIV are 0.6026, 0.6989 and 0.6750 respectively, for the same samples as in Table 2. These are far from one, indicating that OIV and CIV are not substitutes for each other, given the results in Table 2 and 3. We strictly follow the literature (i.e., Guo (2016)) to make our choice of control variables. This finding is robust to controlling for the option delta, time to maturity, and OI.

4.2. Trading strategy based on cross-market information

The mean-reversion investment strategy is based on the assumption that, regardless of the stock's temporary high and low prices, the stock's price tends to achieve average price over a relatively long period. Therefore, investors can buy assets at relatively low prices or sell assets at a higher price to create arbitrage opportunities. We calculate the trading strategy performance based on continuous compounding and a risk-free rate of 2%.

The correlation between 5-year CIV and OIV is 79.98%. As they follow a mean-reversion process and are possibly co-integrated, we construct the following cross-market trading strategy:

$$CIV_{i,t} = \beta_i OIV_{i,t} + \varepsilon_{i,t} \tag{10}$$

To check stationarity, Table 4 reports the results of the standard ADF test for six different variables, i.e., the 5-year CIV-OIV spread, the 5-year CIV-historical realized volatility spread, the OIV-historical realized volatility spread, the 5-year CIV, the OIV, and the historical realized volatility. The results show that the stationarity conditions for different volatilities or spread time series vary widely.

The spread of OIV-historical realized volatilities rank the second and third positions. OIV has a strong correlation with OTM CIV, and the historical realized volatility has a strong correlation with ATM IV. Following Balvers et al. (2000), we standardize the Z-score by $\frac{\varepsilon_{i,t} - u_i(\mathcal{E}_{i,t})}{\sigma_i(\varepsilon_{i,t})}$. Using previous data on each observation time t, we calculate $u_i\left(\varepsilon_{i,t}\right)$ and $\sigma_i\left(\varepsilon_{i,t}\right)$, which are the mean and standard deviation of the error term $(\varepsilon_{i,t})$ at different time t, respectively. Then we sort all of the calculated Z-scores into five quintiles (i.e., 0-20%, 20%-40%, 40%-60%, 60%-80%, 80-100%) at time 0. To be more specific, quintile 1 contains CDS with the lowest Z-scores and thus the most under-valued firms. Quintile 5 contain the CDS with highest Z-scores. We consturct a long-short trading strategy by longing Quintile 1 and shorting Quintile 5 (L1-S5), as well as long positive Z-scores and short negative Z-scores (LP-SN) portfolios.

The fixed 5-year maturity guarantees a trading strategy without a time decay effect relative to the American put option. The Z-score is computed beginning at the 10^{th} observation of the CIV/OIV time series. To determine the CDS return, we use the lognormal return from $\mathrm{S_{t-1}}$ to $\mathrm{S_t}$ and eliminate any observations without a CDS quote at time t-1. The CDS return calculation does not account for transaction costs.

[Insert Table 5 about here]

The trend in the annualized return is gradually decreases from quintile 1 to 5. The L1-S5 trading strategy earns an annualized exponential return of 0.583, beating the 0.412 generated by the LP-SN portfolios, the 0.242 generated by quintile 1 and the 0.118 generated by the trading long negative Z-score strategy (N).

Furthermore, the trading strategies of L1-S5 and LP-SN have much smaller maximum drawdowns (The maximum drawdown is an important risk indicator, which is used to describe the worst possible situation after buying a product. A better trading performance refers to a high Sharpe ratio with a lower maximum drawdown) at 0.099 and 0.084, respectively, and a standard deviation of 0.189 and 0.143, respectively. These two trading strategies also have a great Sharpe Ratio at 2.973 and 2.745, respectively.

[Insert Figure 6 about here]

The performance of the trading strategies of L1-S5 and LP-SN are much better and more stable than those of other strategies and quintiles, even during financial crises. In addition, the cumulative return of quintile 1 is better than those of the other quintiles. The trading strategies of L1-S5 and LP-SN earn a cumulative exponential return of 7.3083 and 5.1575, respectively. From the perspective of drawdown, the trading strategies of long positive (LP), long negative (LN) and quintile 1-5 suffered a large drawdown in the 2009 to 2011 period.

[Insert Figure 7 about here]

The trading strategies of LN-SP and L1-S5 generate higher and more stable cumulative returns than other strategies. It is worth mentioning that in CIV-1, the performance of all of these strategies is stable. At the same time, the cumulative return rate of L1-S5 is as high as 23.7966, far exceeding that of other strategies. The performances of CIV-3, 7 and 10 gradually increase in steadiness.

[Insert Table 6 about here]

Based on different Z-scores constructed using CIV with different maturities. We find that the trend in the annualized return in the quintiles for CIV-1, CIV-3, CIV-7, and CIV-10 is gradually decreasing, which is consistent with the result of CIV-5. The increases in CIV are due to the small Z-score, as CIV is mean-reverting with OIV. As a result, quintile 1 has the smallest Z-score, and the highest annualized return compared to the other groups.

Due to the strongest correlation between CIV-1 and OIV, quintile 1 has not only the highest annualized return of all the portfolios, but also the highest Sharpe ratio. When the CIV is underestimated across different quintiles, the corresponding OIV should be overestimated due to their cointegration. For both trading simple deep OTM puts and taking deep OTM puts delta-Hedging, the weekly returns of the options trading strategies increase from quintile 1 to 5.

[Insert Table 7 about here]

As we are investigating the expected return of OTM American put options based on their volatility characteristics, we hope to reduce the impact of the movements of the underlying assets as much as possible. We find that the yields of both the deep OTM put and deep OTM delta-hedging strategies have a significant trend from low to high. Even when we extend the straddle and call delta-hedging trading strategy to ATM options, the result reveals that the cointegration of CIV and OIV does not mean that the ATM options have been mispriced. Nonetheless, the deep OTM put option leads to mispricing. Changes in the volatility of OTM do not represent volatility changes in ATM. However, there is no significant difference in the yields of the ATM straddle and ATM call delta-hedging strategies, which shows that CIV only has a strong cointegration relationship with OTM-OIV.

4.3. Discussion

This sub-section discusses the possible reasons for our CIV performance.

First of all, CIV and OIV are complementary. CIV better explains OIV than the other way around. The mean values (standard deviations) of CIV and

OIV are 32.18% (18.42%) and 41.67% (17.40%), respectively. Figure 3 shows the time series of the averaged CIV and OIV. Intuitively, we expect that CIV and OIV to share similar upside and downside patterns.

The two main characteristics of the measure developed by Kelly et al. (2019) are corporate leverage and CDS contract maturity. They define $Leverage = \frac{BookDebt}{Marketequity+BookDebt}$, where $BookDebt$ is the sum of short-term and long-term debts. They extract 530 firms over 156 months from the 2002 to 2014 period. We speculate that the structural model in the measure developed by Kelly et al. (2019) focuses on the capital structure, which results in a lower correlation coefficient between CIV and OIV.

The vega risk volatility (volatility innovation) is contracted by ATM straddles (see Appendix B). When using separate factors to regress the long-short CDS returns, skewness and vega risk volatility can significantly explain the CDS returns at the 1% level. When regressing all of the risk factors on CDS returns, the skewness becomes insignificant but the vol remains statistically significant[3].

[Insert Table 8 about here]

In Cremers et al. (2015), the volatility is positively correlated with the returns of the trading strategy, and skewness and the returns of the trading strategy are negatively correlated. Additionally, the correlation coefficient between

[3]**Nonparametric risk-neutral skewness factor**
We define OTM options as OTM call options with 0.25 delta and OTM put options with -0.25 delta, which are $\sigma_{i,call}^{imp}(0.25)$ and $\sigma_{i,\text{ call}}^{imp}(-0.25)$ separately (Bali & Zhou, 2016). Hence, the nonparametric risk-neutral skewness is defined as the difference between the implied volatility from OTM call option and that of the OTM put option.

$$Skew = \sigma_{i,call}^{imp}(0.25) - \sigma_{i,put}^{imp}(-0.25) \tag{11}$$

Nonparametric jump risk proxy
Yan (2011) connects the jump risk to the slope of the implied volatility smile. He proves that S_i is approximately proportional to the product of jump intensity and the average stock jump size.

$$S_i \equiv \sigma_{i,put}^{imp}(-0.5) - \sigma_{i,call}^{imp}(0.5) \approx L_i \lambda_i u_{J_i} \tag{12}$$

λ_i is the jump intensity and u_{Ji} is the average stock jump size. $\sigma_{i,put}^{imp}(-0.5)$ is the implied volatility obtained from the volatility surface with a delta equaling -0.5. $\sigma_{i,call}^{imp}(0.5)$ is the implied volatility obtained from the volatility surface with an delta equaling 0.5. See Appendix C for more details.

the risk factor and the two trading strategies is very low. Nevertheless, the correlation coefficient between the trading strategies of L1-S5 and LN-SP is 0.77.

Moreover, the price revealing processes for CDS, stock, and options markets might also predict OIV using CIV. According to Cao et al. (2010) and Carr & Wu (2011), both the options market and the credit market are inextricably linked to the stock market. Therefore, the information from these two markets will help to predict the stock market trend.

The cointegration relationship between CIV and OIV is the result of the robust link between URC^{CDS} and $URC^{\text{American-put}}$. Whether the URC is constructed with CDS or American put options, there is a stable relationship between them (Carr & Wu, 2011). Once they deviate from this stable relationship, there is an arbitrage opportunity. The URC is a financial product that can be constructed using either CDS or American put options. If URC^{CDS} is undervalued, then investors will buy CDS and sell American put options, resulting in a decrease of $URC^{\text{American-put}}$ and an increase of URC^{CDS}.

In addition, we use the deep OTM implied volatility rather than the ATM implied volatility to further examine the relationship between CIV and OIV, which is illustrated in the cointegration relationship in Table 4. Goyal & Saretto (2009) use the average of the ATM call and put implied volatilities to calculate IV. The historical realized volatility (HRV) and ATM implied volatility have a mean-reversion relationship.

Our calibration method for CIV has a higher correlation with OIV, than the other CIV measures in the literature. Guo (2016) equates the conditional default probability in the CDS valuation with the 5-year default probability of the Merton model, which is problematic as he reveres the equity of CIV by this method and adds leverage to the calibration. Apart from this, our method is generally consistent with Guo (2016). Our calibration method for CIV is different, and we conduct more factor analysis for the returns of a trading strategy. The advantage of our CIV measure is that the correlation coefficient between CIV and OIV is as high as 79.98%, whereas Guo (2016) and Kelly et al.

(2019) only achieve 11.63% and 31.14%, respectively.[4] Therefore, our method is a more accurate measure of equity CIV.

Furthermore, We have appropriately relaxed the screening conditions, especially the strike price. Because we need to verify the result in the transaction, we minimize delta rather than taking extreme values and limit the strike price. Carr & Wu (2011) prove theoretically that either the American put option or CDS spread can be used to construct a URC. They also show that the American put option and CDS are highly correlated, indicating that the relationship is robust. However, they also set less than 5 dollars as a screening criteria for the strike price of the American put option. Thus, their sample is very deep out of money, resulting in fewer screening results (i.e., only about 100 companies). We treat the findings from the weekly ATM trading strategy with caution, as high-frequency trading adds much noise to the market, which may lead to inaccurate results.

Finally, we recheck our trading strategy performance using a different portfolio sorting method. We regress CIV on OIV to obtain the standardized residual and sort the portfolios based on the new Z-scores. The results show a similar but reversed pattern to our main results.

$$OIV_{i,t} = \beta_i CIV_{i,t} + \varepsilon_{i,t} \tag{13}$$

[Insert tables 9 to 11 about here]

Overall, Carr & Wu (2011) method is the most robust for calibrating CIV, and we further improve the method. We get a higher correlation coefficient between CIV and OIV. Both the measures from Kelly et al. (2019) and Guo (2016) have problems because their methods are all based on the Merton model, which is an European-style option pricing method. However, under the same conditions, the implied volatility of an American put option is lower than that of

[4] Guo (2016) provides a similar analysis in his paper. We re-estimate Tables 2, 3 and 5 using the CIV measure proposed in Kelly et al. (2019). See Appendix D for details.

an European put option. Similarly, due to the difference in moneyness and the lower exercise probability of the deep OTM American put option, the implied volatility of the American put option is lower than that of the European put option. Intuitively, an American put option is more likely to explain CDS default events than the European put option. As there is a stronger cointegration relationship between CIV and OIV (i.e, a higher correlation coefficient between them), the returns from our trading strategy is higher than that in Guo (2016).

5. Concluding remarks

There is a robust link between CDS spread and deep OTM American put options. We equal the URC made by CDS spread to the URC of deep OTM American put options for the same company, and hence back out CIV via the binomial tree from deep OTM American put options through a dynamically consistent URC framework.

We evaluate our measure of CIV against the ones in Guo (2016) and Kelly et al. (2019) using the data of weekly U.S. corporate CDS, and OTM put options from our 2002-2014 sample period. We find that our CIV measure is more strongly correlated with the CDS spread. Our CIV measure is much more correlated (with a correlation coefficient of 0.8) with the OIV, and this correction decreases with the maturity difference between the options and CDS of the same company. The value of our CIV measure decreases with the moneyness of the tradable put options, whereas the counterparts in Guo (2016) and Kelly et al. (2019) depend on the moneyness (leverage) of options. Our CIV measure can better explain OIV, and can be better explained by OIV in both the full sample and the subsamples.

We identify a co-integration relationship between our CIV measure and OIV and construct CDS and option trading strategies based on the standardized difference between CIV and OIV. Without taking transaction costs into account, the long-short CDS trading strategy achieves an annualized return of 58.29% and a Sharpe ratio of 2.97 for our 5-year CIV measure, which can not be explained by non-parametric skewness and volatility risk. In terms of options trading strategy, we identify the profitability of the deep OTM put options and deep OTM delta-hedging trading strategies, but not for the ATM straddle, and ATM call delta-hedging trading strategies, which suggests that CIV only has a strong cointegration relationship with the OTM-OIV but not the ATM-OIV. For our CIV measure at all maturity lengthens, we identify a smirk when we plot CIV against the moneyness of tradable put options.

We find that the 1-year CDS is more accurate in estimating the OIV than CDS with other maturities, probably because of less maturity mismatching. CIV-1 is closest to the OIV estimate when the moneyness is less than 0.5, and the highest profitability of the CDS trading strategy based on the Z-score comes from CIV-1.

Our results show that our CIV measure can better capture the dynamics in the credit derivatives markets than other measures and yields strong trading implications. Further research is needed to better understand the information content embedded in CIV, specifically whether CIV can complement the volatility surface and risk-neutral moments implied by options.

One possible caveat of our research is that, we follow the literature (i.e., Carr & Wu (2011)) and explicitly assume the existence of a default corridor [A, B] to facilitate our analysis. This may be a strong assumption and it may be fruitful future direction to check whether there are new insights by relaxing this assumption.

Data Availability Statement:

Data available on request from the authors.

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Table 1: Descriptive statistics (Carr & Wu, 2011 mehod)

Panel A: Summary Statistics							
Variable	Mean	S.D.	Min	0.25	Median	0.75	Max
# of Observations	359.964	198.877	52.000	176.500	360.000	563.500	666.000
Maturity (Day)	545.804	112.194	360.000	451.000	542.000	633.000	969.000
E (Millions)	35018.656	53564.043	119.018	7728.384	16828.140	36388.760	525785.638
D (Millions)	18260.876	73284.227	0.213	1979.322	4338.000	9861.000	916322.000
r (%)	2.715	1.345	0.560	1.580	2.570	3.910	5.230
s	1.400	2.201	0.025	0.355	0.665	1.534	50.467
URC(put)	0.053	0.057	0.001	0.023	0.038	0.061	0.95
URC(CDS)	0.038	0.061	0.001	0.009	0.018	0.042	0.99
CIV (%)	32.179	18.418	8.317	20.237	26.243	37.706	248.799
OIV (%)	41.668	17.405	6.324	30.152	37.406	47.843	228.849
cor (s,CIV)	77.868	19.836	-42.637	70.374	84.136	91.083	98.296
cor (CIV,OIV)	79.984	16.088	-25.405	75.772	84.121	90.495	98.890
moneyness (K/S)	0.589	0.124	0.013	0.520	0.606	0.679	0.984
recovery	0.396	0.026	0.120	0.397	0.400	0.400	0.850
Panel B: CIV Maturity and OIV Moneyness (mean)							
Moneyness (K/S)	1 Year CIV	3 Year CIV	5 Year CIV	7 Year CIV	10 Year CIV	OIV	
0%-100%	0.331	0.300	0.322	0.342	0.367	0.417	
0%-50%	0.584	0.508	0.518	0.529	0.548	0.600	
50%-100%	0.265	0.246	0.271	0.293	0.320	0.369	
cor(CIV, oiv)	0.899	0.889	0.858	0.832	0.806	1.000	
Panel C: Kelly et al. (2019) CIV Statistics							
Variable	Mean	S.D.	Min	0.25	Median	0.75	Max
CIV (%)	44.040	14.595	5.167	35.427	42.909	50.760	295.903
cor(s,CIV)	47.188	38.216	-54.492	21.066	54.693	78.962	99.759
cor(CIV,OIV)	31.144	38.549	-92.722	6.157	37.048	60.151	93.972

Note. This table reports the summary statistics of data from our 2002-2014 sample period. For Panel A, "# of firms" is the total number of firms in the sample, "# of weeks" is the total number of weeks, "# of observations" is the number of observations for each firm, we have 335 firms and 666 weeks in total. 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 5-year 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. Moneyness (K/S) is the ratio, strike price divided by spot equity price. Recovery is declared in credit default claim. For Panel B, the first row reports the mean value of implied volatility from 0% moneyness to 100% moneyness. The second and third rows describe the mean value of implied volatility of low moneyness (0% - 50%) and high moneyness (50% - 100%) separately. The fourth row describes the mean correlation of all CIV and OIV pairs. For Panel C, CIV is the implied volatility of 5-year CDS, calculated from Kelly's method. Cor (CIV, OIV) is the coefficient between Kelly et al. (2019) measure and option implied volatility for each firm.

Table 2: Explain OIV using CIV

	Estimate		*t-stat*	*Estimate*		*t-stat*	*N*
Panel A: Investment-grade							
Constant	0.081	***	9.608	0.046	***	2.638	83
CIV	1.142	***	28.060	1.443	***	23.618	
Delta				-0.708	***	-11.750	
OI				-0.000		-0.419	
Maturity				-0.000	***	-16.423	
Adj R^2	0.667			0.791			
Panel B: Junk-grade							
Constant	0.094	***	15.458	0.090	***	7.330	252
CIV	1.001	***	46.422	1.161	***	32.753	
Delta				-0.510	***	-12.673	
OI				0.000	*	-1.876	
Maturity				0.000	***	-16.997	
Adj R^2	0.663			0.763			
Panel C: Full Sample							
Constant	0.091	***	18.042	0.079	***	7.724	335
CIV	1.036	***	53.528	1.231	***	39.283	
Delta				-0.567	***	-16.408	
OI				0.000	*	-1.918	
Maturity				0.000	***	-21.730	
Adj R^2	0.664			0.770			

Note. This table reports the regression results of regressing CIV on OIV, controlling for other variables such as delta of the option, open interest, and maturity from our 2002-2014 sample period. The adjusted R^2 is shown for each regression. Panels A, B, and C show the results for the investment-grade firms, the junk-grade firms, and the full sample, respectively. N is the total number of firms. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Table 3: Explain CIV using OIV

	Estimate		*t-stat*	*Estimate*		*t-stat*	*N*
Panel A: Investment-grade							
Constant	0.032	***	4.101	0.041	***	4.713	83
OIV	0.603	***	28.575	0.537	***	30.212	
Delta				0.545	***	22.728	
OI				0.000		-0.562	
Maturity				0.000	***	17.821	
Adj R^2	0.667			0.851			
Panel B: Junk-grade							
Constant	0.051	***	7.539	0.049	***	4.944	252
OIV	0.699	***	42.995	0.656	***	39.937	
Delta				0.535	***	19.201	
OI				0.000		0.189	
Maturity				0.000	***	17.561	
Adj R^2	0.663			0.796			
Panel C: Full Sample							
Constant	0.047	***	8.479	0.047	***	6.063	335
OIV	0.675	***	50.091	0.626	***	46.765	
Delta				0.537	***	24.689	
OI				0.000		-0.116	
Maturity				0.000	***	21.842	
Adj R^2	0.664			0.810			

Note. This table reports the regression results of regressing OIV on CIV, controlling for other variables such as the delta of the option, open interest, and maturity from our 2002-2014 sample period. The adjusted R^2 is shown for each regression. Panels A, B, and C show the results for the investment-grade firms, the junk-grade firms, and the full sample, respectively. N is the number of firms. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Table 4: Stationary time series

Variable	Percentage	Number of Companies	Total
Spread of CIV OIV	0.850	285	335
Spread of CIV Hisvol	0.690	232	
Spread of OIV Hisvol	0.460	154	
CIV	0.160	52	
OIV	0.100	32	
HIV	0.020	7	

Note. As indicated in the table, 85% of the companies are in the 5-year CIV-OIV spread showing that there is a strong cointegration relationship from our 2002-2014 sample period. The last three rows, 5-year CIV, OIV, and historical realized volatility account for 16%, 10% and 2% respectively suggesting that there is a serious unit root problem.

Table 5: CDS trading strategy performance using CIV-5 (CIV-OIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	1-5	N-P
Annualized	0.242	0.071	-0.113	-0.188	-0.341	-0.294	0.118	0.583	0.412
Cumulative	3.038	0.888	-1.412	-2.362	-4.271	-3.683	1.477	7.308	5.158
Sharpe Ratio	0.655	0.156	-0.419	-0.664	-1.078	-0.971	0.306	2.973	2.745
S.D.	0.339	0.326	0.316	0.314	0.335	0.324	0.320	0.189	0.143
Max. Draw-down	0.580	0.708	0.849	0.953	0.988	0.979	0.647	0.100	0.084

Note. This table reports the trading performance for each quintile from our 2002-2014 sample period. Two long-short strategies are compared between quintiles. Trading is from April 2002 to December 2014, without accounting for transaction costs.

Table 6: CDS trading strategy using CIV-1, CIV-3, CIV-7, and CIV-10 (CIV-OIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	1-5	N-P
Panel A: CIV-1									
Annualized	0.826	0.013	-0.371	-0.455	-1.072	-0.837	0.220	1.898	1.054
Cumulative	10.361	0.162	-4.651	-5.706	-13.436	-10.459	2.763	23.797	13.175
Sharpe Ratio	1.394	-0.013	-0.775	-0.971	-2.007	-1.733	0.399	3.996	3.631
S.D.	0.579	0.532	0.505	0.489	0.544	0.494	0.502	0.470	0.285
Max. Drawdown	0.592	0.937	0.993	0.998	1.000	1.000	0.755	0.155	0.097
Panel B: CIV-3									
Annualized	0.275	0.033	-0.169	-0.255	-0.539	-0.423	0.070	0.814	0.493
Cumulative	3.447	0.412	-2.114	-3.194	-6.755	-5.294	0.882	10.201	6.165
Sharpe Ratio	0.645	0.035	-0.517	-0.744	-1.411	-1.199	0.137	3.298	2.831
S.D.	0.395	0.372	0.365	0.369	0.396	0.369	0.368	0.241	0.167
Max. Drawdown	0.604	0.814	0.917	0.979	0.999	0.996	0.756	0.290	0.100
Panel C: CIV-7									
Annualized	0.246	0.107	-0.045	-0.151	-0.357	-0.283	0.169	0.604	0.451
Cumulative	3.090	1.343	-0.566	-1.898	-4.478	-3.539	2.118	7.568	5.633
Sharpe Ratio	0.704	0.296	-0.221	-0.597	-1.196	-1.008	0.508	2.929	2.935
S.D.	0.322	0.294	0.294	0.287	0.315	0.300	0.293	0.199	0.147
Max. Drawdown	0.560	0.565	0.736	0.882	0.990	0.975	0.582	0.248	0.101
Panel D: CIV-10									
Annualized	0.408	0.128	-0.008	-0.204	-0.450	-0.301	0.213	0.858	0.512
Cumulative	5.112	1.606	-0.101	-2.549	-5.640	-3.774	2.664	10.752	6.401
Sharpe Ratio	1.313	0.377	-0.091	-0.805	-1.489	-1.047	0.707	3.312	2.587
S.D.	0.295	0.287	0.307	0.278	0.315	0.307	0.273	0.253	0.190
Max. Drawdown	0.491	0.587	0.679	0.935	0.997	0.980	0.576	0.122	0.228

Note. This table reports the trading performance for each quintile from our 2002-2014 sample period. Two long-short strategies are compared between quintiles. Trading is from April 2002 to December 2014, without accounting for transaction costs.

Table 7: Options trading strategy performance(CIV-OIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	5-1	P-N
Panel A: Deep OTM put									
Annualized	-1.605	-1.359	-1.086	-0.927	-0.234	-0.648	-1.453	1.371	0.806
Cumulative	-20.159	-17.070	-13.621	-11.643	-2.937	-8.127	-18.244	17.222	10.105
Sharpe Ratio	-1.967	-1.683	-1.326	-1.130	-0.293	-0.788	-1.826	3.435	2.837
S.D.	0.826	0.819	0.834	0.838	0.866	0.848	0.807	0.393	0.277
Max. Drawdown	1.000	1.000	1.000	1.000	0.996	1.000	1.000	0.547	0.350
Panel B: Deep OTM put delta-hedging									
Annualized	-0.165	-0.088	-0.029	-0.005	0.179	0.083	-0.123	0.343	0.205
Cumulative	-2.071	-1.105	-0.363	-0.064	2.242	1.036	-1.540	4.313	2.576
Sharpe Ratio	-1.689	-1.025	-0.450	-0.230	1.189	0.508	-1.387	3.801	3.074
S.D.	0.109	0.105	0.109	0.109	0.133	0.123	0.103	0.085	0.060
Max. Drawdown	0.906	0.766	0.549	0.459	0.261	0.391	0.840	0.082	0.051
Panel C: ATM straddle									
Annualized	-2.525	-2.627	-2.589	-2.615	-2.694	-2.643	-2.566	-0.185	-0.087
Cumulative	-31.707	-32.789	-32.362	-32.839	-33.774	-33.094	-32.225	-2.316	-1.094
Sharpe Ratio	-4.334	-4.564	-4.233	-4.339	-4.547	-4.786	-4.709	-0.503	-0.367
S.D.	0.587	0.580	0.616	0.607	0.597	0.557	0.549	0.407	0.293
Max. Drawdown	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.948	0.846
Panel D: ATM call delta-hedging									
Annualized	0.035	0.047	0.030	0.061	0.047	0.037	0.046	0.013	-0.008
Cumulative	0.445	0.593	0.376	0.769	0.591	0.467	0.581	0.163	-0.097
Sharpe Ratio	0.169	0.340	0.122	0.548	0.335	0.230	0.350	-0.096	-0.528
S.D.	0.092	0.081	0.082	0.075	0.081	0.075	0.075	0.072	0.053
Max. Drawdown	0.260	0.144	0.210	0.180	0.199	0.185	0.164	0.151	0.178

Note. from our 2002-2014 sample period, the returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price. The hedge ratio for the delta-hedged puts is calculated using the current IV estimate. The options weekly returns are equal-weighted (for quintiles) (for P and N portfolios) across all the stocks in the portfolio. The sample includes 335 stocks and is composed of 108,449 weekly deep OTM put contracts and 136,928 weekly ATM pairs of call and put contracts. The sample period is 2002 to 2014.

Table 8: Explain risk-adjusted long-short CDS returns

Panel A: Explain risk-adjusted long-short CDS returns										
	Skewness (1)		Yan jump (2)		Cremer's jump (3)		Cremer's volatility (4)		Skewness+ volatility (5)	
Constant	0.004		0.011	***	0.013	***	0.013	***	0.008	***
	-1.304		-8.230		-7.956		-8.184		-2.854	
	-1.304		-8.230		-7.956		-8.184		-2.854	
Skewness	-0.140	**							-0.086	
	(-2.391)								(-1.390)	
Jump			0.020		-0.014					
			-1.291		(-0.366)					
Vol							0.146	***	0.135	***
							-4.216		-3.441	
Adj R^2	0.023		0.005		-0.001		0.028		0.035	

Panel B: Pearson correlation coefficients matrix						
	L1. S5	Ln. Sp	skewness	Cremers'jump	Cremers'vol	Yan.jump
L1. S5	1.000	0.770	-0.120	-0.030	0.170	0.060
Ln. Sp		1.000	-0.090	-0.060	0.110	0.030
skewness			1.000	0.020	-0.130	-0.360
Cremers'jump				1.000	0.290	-0.010
Cremers'vol					1.000	-0.010
Yan.jump						1.000

Note. This table reports the regression results we obtain when we attempt to explain risk-adjusted long-short CDS returns from our 2002-2014 sample period. Skewness is a nonparametric risk-neutral risk factor constructed using OTM implied volatilities (Bali & Zhou, 2016). Yan's Jump is a nonparametric risk-neutral jump risk factor constructed by ATM implied volatilities (Yan, 2011). Cremers' Jump and Volatility are tradable aggregate volatility and jump risk proxies constructed by ATM straddles (Cremers et al., 2015). We report t statistics in square parentheses, and ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively. L1. S5 represents the time series of the weekly return of the trading strategy by long first quintile and short fifth quintile, while Ln. Sp represents that by long negative portfolio and short positive portfolio.

Table 9: CDS trading strategy performance using CIV-5 (OIV-CIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	5-1	P-N
Annualized	-0.339	-0.200	-0.103	0.066	0.246	0.124	-0.296	0.585	0.420
Cumulative	-4.249	-2.505	-1.293	0.823	3.081	1.556	-3.701	7.330	5.256
Sharpe Ratio	-1.074	-0.699	-0.397	0.137	0.663	0.325	-0.976	2.953	2.783
S.D.	0.334	0.315	0.310	0.332	0.340	0.320	0.323	0.191	0.144
Max. Drawdown	0.988	0.951	0.849	0.718	0.588	0.627	0.979	0.097	0.085

Note. This table reports the trading performance for each quintile from our 2002-2014 sample period. Two long-short strategies are compared between quintiles. Trading is from April 2002 to December 2014, without accounting for transaction costs.

Table 10: CDS trading strategy using CIV-1, CIV-3, CIV-7, and CIV-10 (OIV-CIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	5-1	P-N
Panel A: CIV-1									
Annualized	-1.051	-0.464	-0.393	0.046	0.831	0.219	-0.838	1.882	1.053
Cumulative	-13.176	-5.815	-4.920	0.576	10.426	2.741	-10.470	23.602	13.164
Sharpe Ratio	-2.103	-0.991	-0.819	0.048	1.399	0.395	-1.736	4.290	3.627
S.D.	0.509	0.488	0.504	0.537	0.580	0.503	0.494	0.434	0.285
Max. Draw-down	1.000	0.998	0.995	0.931	0.595	0.739	1.000	0.246	0.097
Panel B: CIV-3									
Annualized	-0.551	-0.242	-0.167	0.025	0.272	0.078	-0.434	0.823	0.512
Cumulative	-6.907	-3.038	-2.097	0.318	3.417	0.979	-5.436	10.323	6.404
Sharpe Ratio	-1.476	-0.711	-0.516	0.014	0.631	0.158	-1.233	3.553	2.961
S.D.	0.387	0.369	0.363	0.380	0.400	0.368	0.368	0.226	0.166
Max. Draw-down	0.999	0.976	0.919	0.809	0.618	0.741	0.996	0.191	0.094
Panel C: CIV-7									
Annualized	-0.365	-0.133	-0.052	0.079	0.271	0.163	-0.282	0.636	0.444
Cumulative	-4.575	-1.670	-0.649	0.993	3.397	2.046	-3.528	7.972	5.550
Sharpe Ratio	-1.223	-0.534	-0.244	0.190	0.793	0.490	-1.005	3.144	2.872
S.D.	0.315	0.287	0.295	0.312	0.316	0.293	0.300	0.196	0.148
Max. Draw-down	0.991	0.881	0.755	0.568	0.558	0.583	0.975	0.115	0.101
Panel D: CIV-10									
Annualized	-0.450	-0.162	-0.040	0.136	0.403	0.213	-0.293	0.853	0.503
Cumulative	-5.640	-2.028	-0.498	1.703	5.054	2.662	-3.665	10.694	6.290
Sharpe Ratio	-1.532	-0.613	-0.208	0.403	1.295	0.705	-1.020	3.443	2.531
S.D.	0.307	0.297	0.287	0.287	0.296	0.273	0.307	0.242	0.191
Max. Draw-down	0.997	0.924	0.710	0.566	0.504	0.578	0.977	0.117	0.228

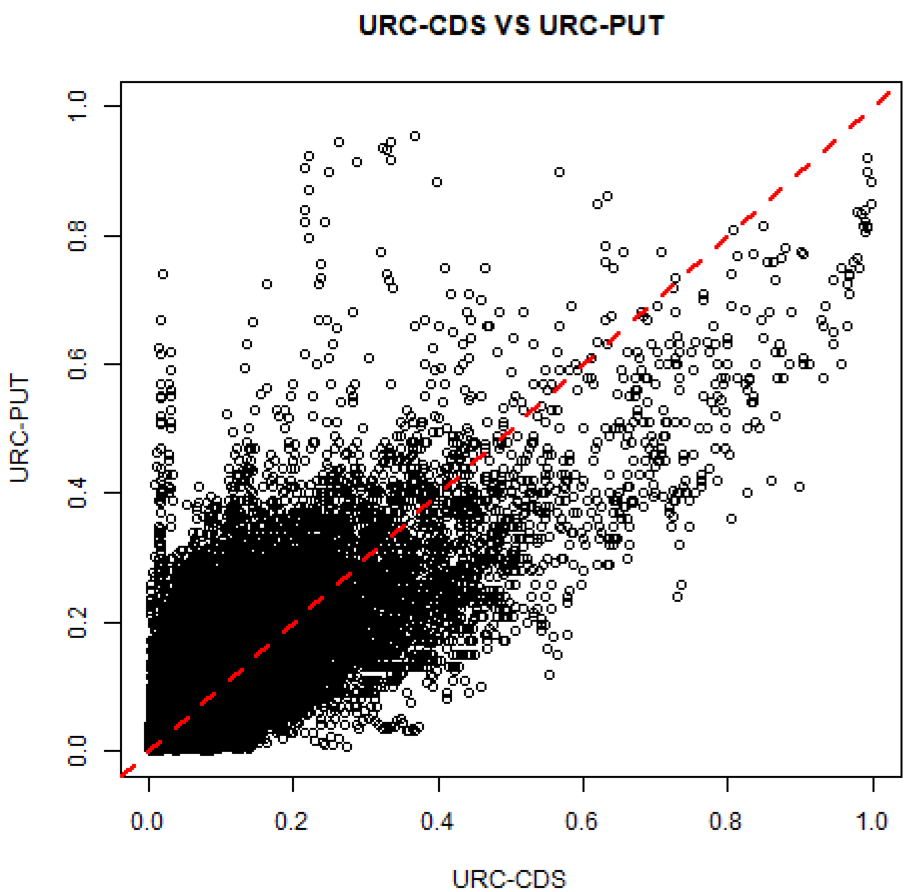
Note. This table reports the trading performance for each quintile from our 2002-2014 sample period. Two long-short strategies are compared between the quintiles, without accounting for transaction costs.

Table 11: Options trading strategy performance (OIV-CIV)

	Quintile portfolios								
	1	2	3	4	5	P	N	1-5	N-P
Panel A: Deep OTM put									
Annualized	-0.216	-0.930	-1.122	-1.351	-1.608	-1.472	-0.637	1.392	0.836
Cumulative	-2.712	-11.679	-14.073	-16.970	-20.187	-18.480	-7.988	17.475	10.481
Sharpe Ratio	-0.273	-1.136	-1.370	-1.673	-1.964	-1.848	-0.775	3.458	2.916
S.D.	0.865	0.836	0.834	0.820	0.829	0.807	0.847	0.397	0.280
Max. Draw-down	0.995	1.000	1.000	1.000	1.000	1.000	1.000	0.538	0.350
Panel B: Deep OTM put delta-hedging									
Annualized	0.177	0.005	-0.036	-0.089	-0.166	-0.128	0.087	0.344	0.216
Cumulative	2.225	0.065	-0.449	-1.121	-2.090	-1.613	1.092	4.315	2.705
Sharpe Ratio	1.181	-0.136	-0.517	-1.040	-1.692	-1.435	0.545	3.793	3.197
S.D.	0.133	0.109	0.108	0.105	0.110	0.103	0.123	0.085	0.061
Max. Draw-down	0.264	0.441	0.554	0.759	0.908	0.851	0.381	0.087	0.051
Panel C: ATM straddle									
Annualized	-2.701	-2.622	-2.566	-2.632	-2.542	-2.573	-2.640	-0.174	-0.077
Cumulative	-33.867	-32.878	-31.976	-33.004	-31.872	-32.311	-33.055	-2.182	-0.969
Sharpe Ratio	-4.557	-4.409	-4.198	-4.538	-4.359	-4.710	-4.791	-0.473	-0.335
S.D.	0.597	0.599	0.616	0.585	0.588	0.551	0.555	0.411	0.290
Max. Draw-down	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.957	0.833
Panel D: ATM call delta-hedging									
Annualized	0.052	0.048	0.038	0.048	0.038	0.045	0.039	0.015	-0.005
Cumulative	0.653	0.605	0.475	0.607	0.477	0.569	0.487	0.186	-0.065
Sharpe Ratio	0.403	0.356	0.225	0.363	0.194	0.336	0.253	-0.072	-0.480
S.D.	0.080	0.079	0.080	0.078	0.093	0.075	0.075	0.072	0.053
Max. Draw-down	0.199	0.199	0.180	0.147	0.264	0.166	0.176	0.151	0.172

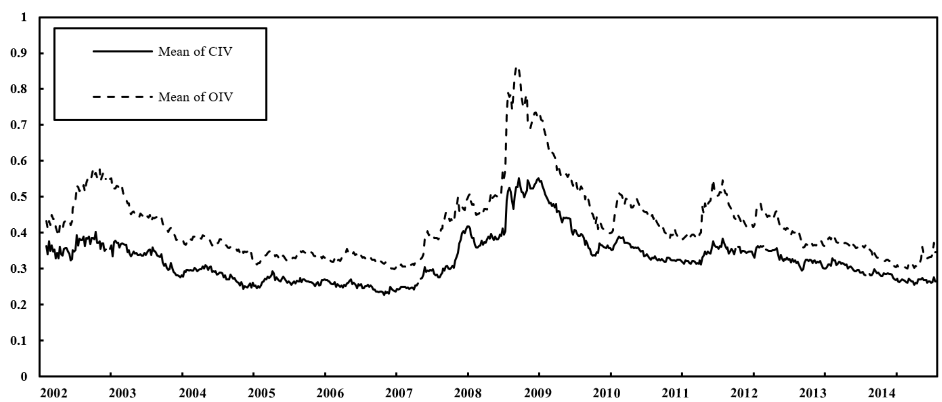
Note. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price from our 2002-2014 sample period. The hedge ratio for the delta-hedged puts is calculated using the current IV estimate. The options weekly returns are equal-weighted (for quintiles) (for P and N portfolios) across all of the stocks in the portfolio. The sample includes 335 stocks and is composed of 108449 weekly deep OTM put contracts and 136928 weekly ATM pairs of call and put contracts.

Figure 1: Scatter of URC (CDS) Vs URC (Put)



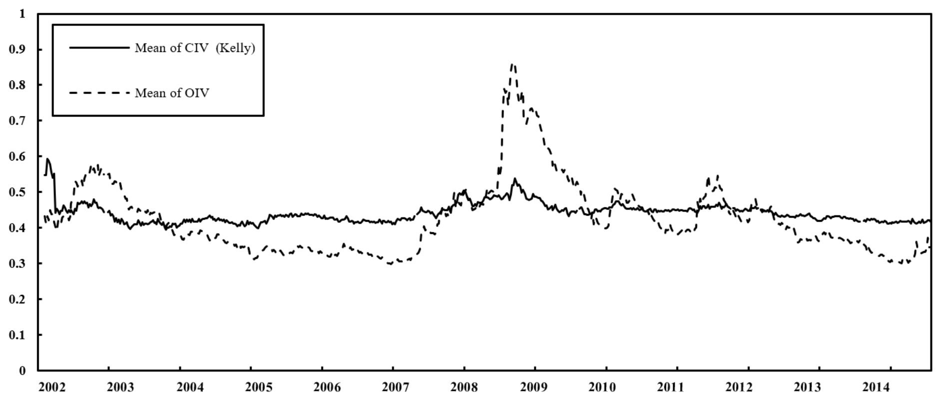
Note. This figure shows the scatter plot of the URC (CDS) and URC (Put option) from our 2002-2014 sample period.

Figure 2: Mean values of our CIV measure and OIV



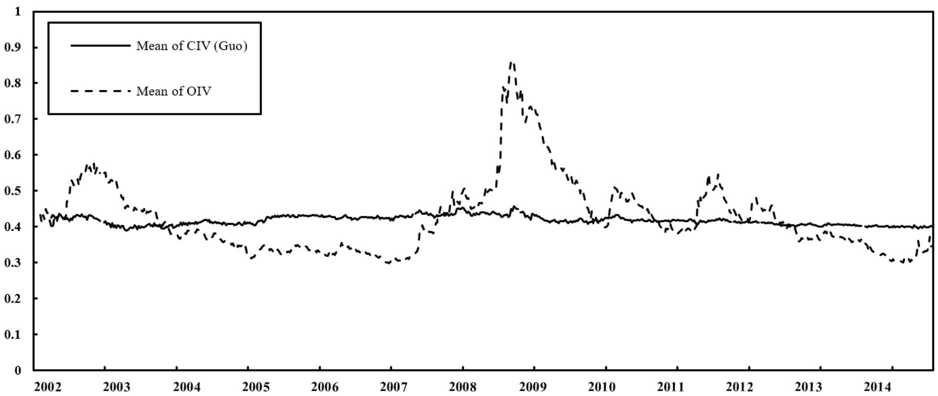
Note. This figure shows the time series of the averaged CIV (our measure) and OIV from our 2002-2014 sample period.

Figure 3: Mean values of the CIV and OIV (Kelly et al., 2019)



Note. This figure shows the time series of the averaged CIV (Kelly et al., 2019) and OIV from our 2002-2014 sample period.

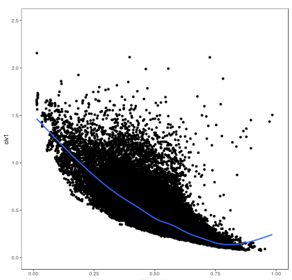
Figure 4: Mean values of CIV and OIV (Guo, 2016)



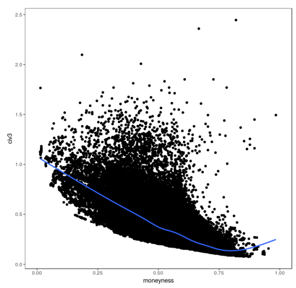
Note. This figure shows the time series of the averaged CIV from Guo (2016) and OIV from our 2002-2014 sample period.

Figure 5: Credit implied volatility smirk (heterogeneity-adjusted)

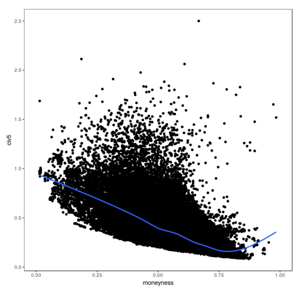
(a) 1-Year CIV



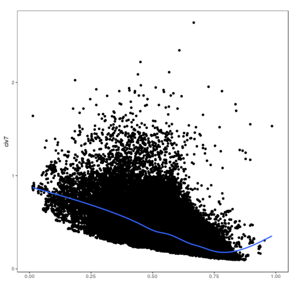
(b) 3-Year CIV



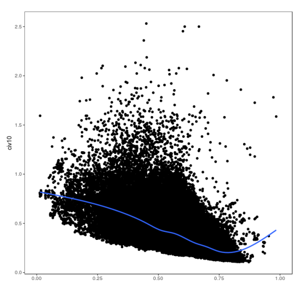
(c) 5-Year CIV



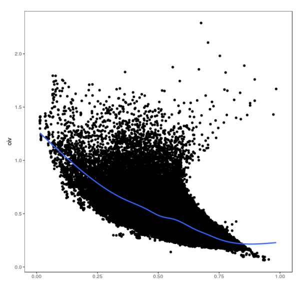
(d) 7-Year CIV



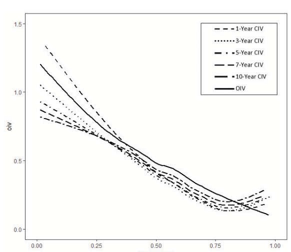
(e) 10-Year CIV



(f) OIV

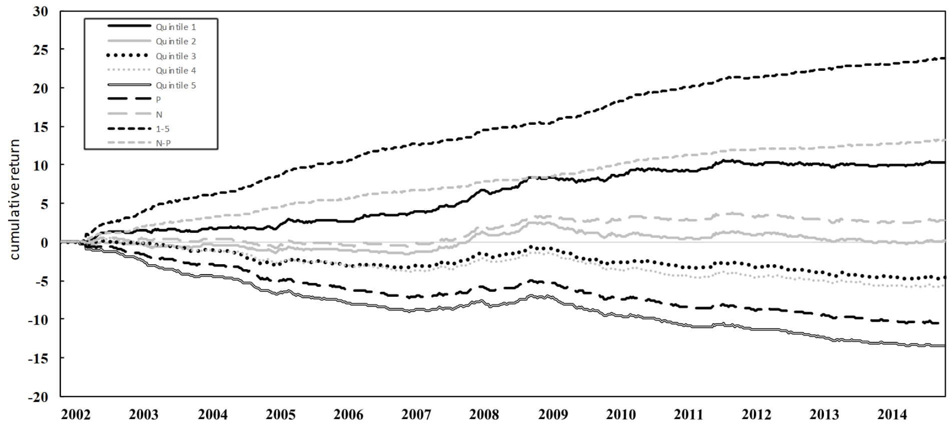


(g) Implied Volatility



Note. Pooled scatter plots of weekly CIV versus moneyness (K/S) from our 2002-2014 sample period. The blue line is a fitted non-parametric curve. The lower left panel overlays the fitted CIV/OIV curve at all moneyness values to trace out the CIV/OIV surface.

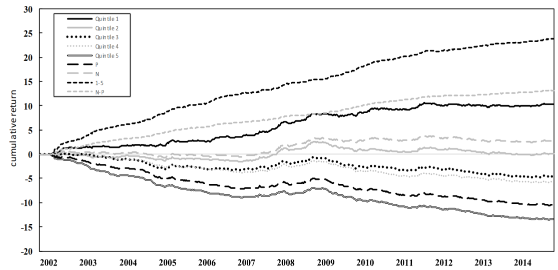
Figure 6: Cumulative returns of the trading strategies



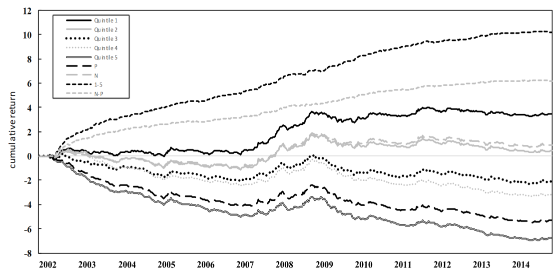
Note. This figure demonstrates the cumulative returns of the trading strategies for the 5-year CIV from our 2002-2014 sample period.

Figure 7: Cumulative returns of trading strategies from top to bottom: CIV-1, CIV-3, CIV-7, and CIV-10

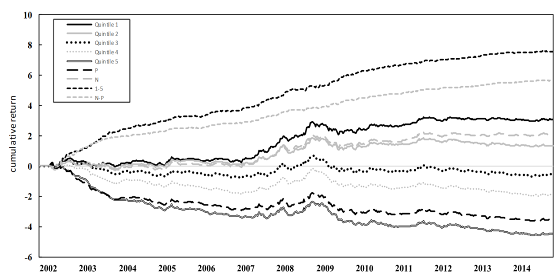
(a) 1-Year CIV



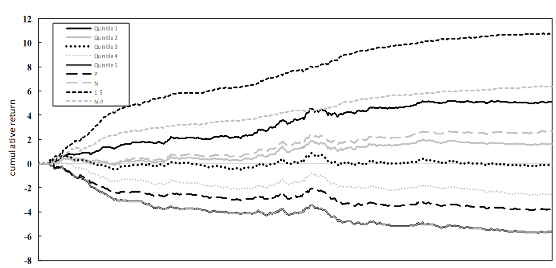
(b) 3-Year CIV



(c) 7-Year CIV



(d) 10-Year CIV



Notes. This figure shows the robust cumulative returns of the trading strategies from our 2002-2014 sample period.

Appendix

A. Relationship between CDS and Deep OTM put

Assume two independent random variables are defined on the probability space $(\Omega, \mathcal{G}, \mathbb{Q})$, a standard Brownian motion $\{W_t, t \geq 0\}$ generating a filtration $\mathbb{F} = \{\mathcal{F}_t, t \geq 0\}$, and an exponential random variable with unit parameter $\xi \sim Exp(1)$. Following Carr & Linetsky (2006) and Carr & Wu (2011), the stock can either diffuse or jump to default, a predictable part and a totally inaccessible part. In the first case, default occurs at $T_0 \in (0, \infty)$, the first hitting time of the stock S_t to $Be^{\int_0^t r_u du}$ where $B < S_0$. Upon default, the stock price is sent to a residue recovery state Δ governed by an adapted process R_t bounded above by $A < B$ over the time interval $[0, T]$. The state space of the stock price process is therefore $(B, \infty) \cup \{\Delta\}$.

The time of jump to default $\tilde{\eta}$ is modeled by the first hitting time of the hazard process Λ to the exponential random variable ξ:

$$\tilde{\eta} = \inf\{t \geq 0 : \Lambda_t \geq e\} \tag{A.1}$$

where Λ is defined as:

$$\Lambda_t = \begin{cases} \int_0^t \lambda_u du, & t < T_0 \\ \infty, & t \geq T_0 \end{cases} \tag{A.2}$$

and λ_t denotes the time-varying jump intensity process. The time of default η is:

$$\eta = \tilde{\eta} \wedge T_0 \tag{A.3}$$

Following Elliott et al. (2000), we denote the default process $\{N_t, t \geq 0\}$, $N_t = \mathbb{1}_{\eta \leq t}$, generating a filtration $\mathbb{H} = \{\mathcal{H}_t, t \geq 0\}$. Together with $\mathbb{F}$ generated by the Brownian motion W_t, an enlarged filtration can be defined as $\mathcal{G}_t = \mathcal{F}_t \vee \mathcal{H}_t$.

Putting everything together, the stock price process can be modeled as follows:

$$S_t = (1 - J_t)R_t + e^{\int_0^t r_u du} J_t \left(B + (S_0 - B)G_t\right) \tag{A.4}$$

where $G_t = e^{\sigma_t W_t - \sigma_t^2 t/2}$ and $J_t = \mathbb{1}_{N_t=0} e^{\int_0^t \lambda_u du}$ are $\mathcal{F}$- and $\mathcal{H}$- adapted martingales, respectively. Carr & Wu (2011) show that the risk-neutral pre-default stock price process is governed by the stochastic process:

$$\begin{aligned} dS_t =& \left((r_t + \lambda_t)(S_t - R_t) + r_t R_t e^{\int_0^t \lambda_u du} \right) dt \\ &+ \left(S_t - R_t - e^{\int_0^t \lambda_u du} \left(B e^{\int_0^t r_u du} - R_t \right) \right) \sigma_t dW_t \end{aligned} \tag{A.5}$$

Without explicitly assuming the processes for R_t, r_t, λ_t and σ_t, we only note that they are time-varying.

The price of an American put option $P_t^d(K)$ with strike $K > Be^{-\int_0^T r_u du}$ can be derived from the risk-neutral dynamic of S_t such that:

$$\begin{aligned} P_t(K) =& \mathbb{E}_t^{\mathbb{Q}} \left[\max \left(e^{-\int_t^\eta r_u du}(K - R_\eta)^+, \sup_{\varphi \in \phi(\eta)} \mathbb{E} \left[e^{-\int_t^\varphi r_u du}(K - S_\varphi)^+ \right] \right) \mathbb{1}_{\eta \le T} \right] \\ &+ \sup_{\psi \in \phi(T)} \mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^\psi r_u du}(K - S_\psi)^+ \mathbb{1}_{\eta > T} \right] \end{aligned} \tag{A.6}$$

where $\phi(\tau)$ denotes the set of stopping times $\varphi \in [t, \tau]$ and expectations are conditional with respect to the σ-algebra $\mathcal{G}_t$. We can rewrite this equation to a more familiar form:

$$\begin{aligned} P_t(K) =& \sup_{\psi \in \phi(T)} \mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^\psi r_u du}(K - S_\psi)^+ \mathbb{1}_{\eta > T} \right] \\ &+ \mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^\eta r_u du}(K - R_\eta)^+ \mathbb{1}_{\eta \le T} \right] \\ &+ \mathbb{E}_t^{\mathbb{Q}} \left[\left(\sup_{\varphi \in \phi(\eta)} \mathbb{E}_t^{\mathbb{Q}} \left[e^{-\int_t^\varphi r_u du}(K - S_\varphi)^+ \right] - e^{-\int_t^\eta r_u du}(K - R_\eta)^+ \right)^+ \mathbb{1}_{\eta \le T} \right] \end{aligned} \tag{A.7}$$

The first term can be rewritten as the conditional expectation with respect to the stock price:

$$\begin{aligned}
&\sup_{\psi\in\phi(T)} \mathbb{E}_t^{\mathbb{Q}}\left[e^{-\int_t^{\psi} r_u du}(K-S_\psi)^+\mathbb{1}_{\eta>T}\,\middle|\,\mathcal{G}_t\right]\\
=&\sup_{\psi\in\phi(T)} \mathbb{E}_t^{\mathbb{Q}}\left[e^{-\int_t^{\psi}[\lambda_u+r_u]du}(K-S_\psi)^+\mathbb{1}_{\{m_{t,T}^S\geq Be^{\int_0^t r_u du}\}}\,\middle|\,S_t=S\right]\\
=&P_t^o(K)
\end{aligned} \tag{A.8}$$

and

$$m_{t,T}^S=\inf_{s\in[t,T]} S_s e^{-\int_0^{s-t} r_u du}. \tag{A.9}$$

This term represents an American down-and-out barrier put option, the portion of the put option price corresponding to the market risk above the barrier $Be^{\int_0^s r_u du}$ at any time $s\in[t,T]$. Note that if K is below B, this term reduces to zero.

The second term can also be expressed in terms of a risk-neutral expectation conditional on S_t, separating the diffuse to default and the jump-induced default:

$$\begin{aligned}
&\mathbb{E}_t^{\mathbb{Q}}\left[e^{-\int_t^{\eta} r_u du}(K-R_\eta)^+\mathbb{1}_{\eta\leq T}\,\middle|\,\mathcal{G}_t\right]\\
=&\mathbb{1}_{\eta>t}\int_t^T e^{-\int_t^v r_u du}\mathbb{E}_t^{\mathbb{Q}}\left[e^{-\int_t^v \lambda_u du}\lambda_v(K-R_v)^+\mathbb{1}_{\{m_{t,v}^S\geq Be^{\int_0^t r_u du}\}}\,\middle|\,S_t\right]dv\\
&+\mathbb{1}_{\eta>t}\mathbb{E}_t^{\mathbb{Q}}\left[e^{-\int_t^{T_0}[\lambda_u+r_u]du}(K-R_{T_0})^+\mathbb{1}_{t<T_0<T}\,\middle|\,S_t\right]\\
=&P_t^d(K)
\end{aligned} \tag{A.10}$$

This term represents the default sensitive portion of the option price, which only takes a positive value if $K>R_\eta$ at the time of default. Assuming that R_t is constant and equals to the lower bound of the default corridor A, this term can be related to URC as follows:

$$P_t^d(K)=(K-A)URC(t,T) \tag{A.11}$$

The third term can be expressed as conditional expectations in the same fashion as in Term One and Two. It represents the decision to exercise early the option before default. Note that if the strike price K falls within the default barrier $[B, A]$, it is never optimal to exercise early. If K is well above $Be^{\int_0^T r_u du}$, the option buyer may exercise early while walking away from the default-related option premium.

Denoting the third term as $P_t^e(K)$, the put option can be simply decomposed as follows:

$$P_t(K) = P_t^o(K) + P_t^d(K) + P_t^e(K) \tag{A.12}$$

This decomposition is parallel to the pricing formula for European options obtained in Carr & Linetsky (2006). Indeed, on top of the default risk, a put option struck outside of the default corridor also depends on the price dynamic of the underlying stock. Assume that two put options are available one with strike K_1 above $Be^{\int_0^T r_u du}$, the other with strike $K_2 \in [B, A]$. The URC can be expressed in terms of these two option prices as follows:

$$URC^p = \frac{P_t^d(K_1) - P_t(K_2)}{K_1 - K_2} = \frac{P_t(K_1) - P_t(K_2) - (P_t^o(K) + P_t^e(K))}{K_1 - K_2} \tag{A.13}$$

Assuming that K_2 and $P_t(K_2)$ are small enough to be negligible, and equating the URC implied by the put option to the one implied by the CDS spread, our definition of the CDS-equivalent put option price has the following functional form:

$$P_t^{\text{CDS}}(K) = URC_t^{\text{CDS}} K = P_t(K) - (P_t^o(K) + P_t^e(K)) \tag{A.14}$$

when K is well above the default barrier. As argued earlier, the problem of a deep out-of-the money put struck outside of the default corridor is likely to be an issue for a well-established firm with large market capitalization where the put option contains not only the credit-related claims, but also market-price-related claims between K_1 and B; $P_t^{\text{CDS}}(K)$ inferred from CDS spread is the credit-risk component of the OTM put option premium without any information about market risk. We therefore anticipate that the OIV will be explained by the CDS implied volatility, but not the other way around.

B. Heston model and a tradable proxy for volatility risk

Cremers et al. (2015) propose that instantaneous excess straddle returns are proportional to innovations in volatility in the Heston (1993) stochastic volatility model. Assume that the asset price S_t at time t and its variance V_t follow the diffusion processes

$$dS_t = (\mu - \delta)S_t dt + S_t \sqrt{V_t} dZ_{1t}, \tag{B.1}$$

$$dV_t = k(\theta - V_t)\, dt + \sigma \sqrt{V_t} dZ_{2t}, \tag{B.2}$$

where Z_{1t} and Z_{2t} are P-Brownian motions with correlation ρ, and δ is the dividend yield.

Equation (B.2) shows that the value of any derivative $U(S_t, V_t, t)$ must satisfy the partial differential equation (PDE) below:

$$\frac{1}{2}V_t S_t^2 \frac{\partial^2 U}{\partial S^2} + \rho\sigma V_t S_t \frac{\partial^2 U}{\partial S \partial V} + \frac{1}{2}\sigma^2 V_t \frac{\partial^2 U}{\partial V^2} + (r-\delta)S_t \frac{\partial U}{\partial S} + [k(\theta - V_t) - \lambda(S_t, V_t, t)] \frac{\partial U}{\partial V} + \frac{\partial U}{\partial t} = rU \tag{B.3}$$

where $\lambda(S_t, V_t, t)$ is the market price of volatility risk.

According to Ito's Lemma,

$$dU = \left[\frac{1}{2}V_t S_t^2 \frac{\partial^2 U}{\partial S^2} + \rho\sigma V_t S_t \frac{\partial^2 U}{\partial S \partial V} + \frac{1}{2}\sigma^2 V_t \frac{\partial^2 U}{\partial V^2} + \frac{\partial U}{\partial t}\right] dt + \frac{\partial U}{\partial V} dV_t + \frac{\partial U}{\partial S} dS_t. \tag{B.4}$$

Substituting the drift term with the PDE, we get

$$\begin{aligned} dU &= rUdt - (r-\delta)S_t \frac{\partial U}{\partial S} dt - [k(\theta - V_t) - \lambda(S_t, V_t, t)] \frac{\partial U}{\partial V} dt + \frac{\partial U}{\partial V} dV_t + \frac{\partial U}{\partial S} dS_t \\ &= rUdt + \frac{\partial U}{\partial S}[dS_t - (r-\delta)S_t dt] + \frac{\partial U}{\partial V}\{dV_t - [k(\theta - V_t) - \lambda(S_t, V_t, t)]\, dt\} \end{aligned}. \tag{B.5}$$

Therefore, instantaneous option returns satisfy the following

$$\frac{dU}{U} = rdt + \frac{\partial U}{\partial S}\frac{S_t}{U}\left[\frac{dS_t}{S_t} - (r-\delta)dt\right] + \frac{\partial U}{\partial V}\frac{1}{U}\{dV_t - [k(\theta - V_t) - \lambda(S_t, V_t, t)]\, dt \tag{B.6}$$

Let STR denote the price of a delta-neutral straddle, then the instantaneous straddle returns satisfy the following

$$\frac{dSTR}{STR} = rdt + \frac{\partial STR}{\partial V}\frac{1}{STR}dV_t - \frac{\partial STR}{\partial V}\frac{1}{STR}\left[k\left(\theta - V_t\right) - \lambda\left(S_t, V_t, t\right)\right]dt, \tag{B.7}$$

or

$$\frac{dSTR}{STR} = rdt + \frac{\partial STR}{\partial V}\frac{1}{STR}\left[dV_t - \mathbb{E}_t^{\mathbb{Q}}\left(dV_t\right)\right], \tag{B.8}$$

where $\mathbb{Q}$ is the equivalent martingale measure, which implies that (excess) straddle returns are locally proportional to innovations in volatility.

C. Bates model and a tradable proxy for jump risk

Under P-measure

$$dS_t = \mu S_t dt + \sigma_t dW_t^1 \tag{C.1}$$

or with jump

$$dS_t = \mu S_t dt + \sigma_t dW_t^1 + (J-1) S_t dq_t \tag{C.2}$$

$$\begin{aligned} dV_t &= k\left(\overline{V} - V_t\right) dt + \sigma_V \sqrt{(V_t)} dW_t^2 \\ \log(J) &\sim N\left(\mu_*, \sigma_*^2\right) \\ dW_t^1 dW_t^2 &= \rho dt \end{aligned} \tag{C.3}$$

Under Q-measure

$$dV_t^Q = \left[k\left(\overline{V} - V_t\right) - \lambda\right] dt + \sigma_V \sqrt{(V_t)} dW_t^{2,Q} \tag{C.4}$$

Then, we form the portfolio $\pi = U - \Delta S$ where U is the derivatives.

Merton (1976) argues that the jump risk is irrelevant to the market, as the jump risk can be diversified, i.e., $E(d\pi) = r\pi dt$.

$$\begin{aligned} \because d\pi &= dU - \Delta dS \\ &= \frac{\partial U}{\partial t} dt + \frac{\partial U}{\partial S} dS + \frac{\partial U}{\partial V_t} dV_t^Q + \frac{1}{2}\left[\frac{\partial^2 U}{\partial S^2}(dS)^2 + 2\frac{\partial^2 U}{\partial S \partial V_t} dS dV_t^Q + \frac{\partial^2 U}{\partial V_t^2} dV_t^2 - \frac{\partial U}{\partial S} dS\right] + \\ &\quad \{[U(JS,t) - \Delta JS] - [U(S,t) - \Delta S]\} dq \\ &= \left[\frac{\partial U}{\partial t} + \frac{1}{2}\frac{\partial^2 U}{\partial S^2}\sigma^2 S^2 + \sigma_V S V_t \frac{\partial^2 U}{\partial S \partial V_t} + \frac{1}{2}\sigma_v^2 V_t \frac{\partial^2 U}{\partial V_t^2}\right] dt + \frac{\partial U}{\partial V_t} dV_t^Q + \\ &\quad \{[U(JS,t) - \Delta JS] - [U(S,t) - \Delta S]\} dq \end{aligned} \tag{C.5}$$

$$\therefore E(d\pi) = \left[\frac{\partial U}{\partial t} + \frac{1}{2}\frac{\partial^2 U}{\partial S^2}\sigma^2 S^2 + \sigma_V S V_t \frac{\partial^2 U}{\partial S \partial V_t} + \frac{1}{2}\sigma_v^2 V_t \frac{\partial^2 U}{\partial V_t^2}\right] dt + \frac{\partial U}{\partial V_t}\left[k\left(\overline{V} - V_t\right) - \lambda\right] dt +$$
$$E\{[U(JS,t) - \Delta JS] - [U(S,t) - \Delta S]\}\lambda dt$$
$$= r\left(U - \frac{\partial U}{\partial S} S\right) dt \tag{C.6}$$

The PDE function is:

$$\therefore rU = \frac{\partial U}{\partial t} + \frac{1}{2}\frac{\partial^2 U}{\partial S^2}\sigma^2 S^2 + \sigma_V S V_t \frac{\partial^2 U}{\partial S \partial V_t} + \frac{1}{2}\sigma_v^2 V_t \frac{\partial^2 U}{\partial V_t^2} + rS\frac{\partial U}{\partial S} + \left[k\left(\overline{V} - V_t\right) - \lambda\right]\frac{\partial U}{\partial V_t} -$$
$$\lambda E\{[U(JS,t) - \Delta JS] - [U(S,t) - \Delta S]\} \tag{C.7}$$

Calculate dU by PDE

$$\because dU = \frac{\partial U}{\partial t} dt + \frac{\partial U}{\partial S} dS + \frac{\partial U}{\partial V_t} dV_t + \frac{1}{2}\left(\frac{\partial^2 U}{\partial S^2}\sigma^2 S^2 dt + 2\sigma_V S V_t \frac{\partial^2 U}{\partial S \partial V_t} dt + \sigma_V^2 V_t \frac{\partial^2 U}{\partial V_t^2} dt\right) +$$
$$[U(JS,t) - U(S,t)]dq$$
$$= [\frac{\partial U}{\partial t} + \frac{1}{2}\frac{\partial^2 U}{\partial S^2}\sigma^2 S^2 + \sigma_V S V_t \frac{\partial^2 U}{\partial S \partial V_t} + \frac{1}{2}\sigma_V^2 V_t \frac{\partial^2 U}{\partial V_t^2}]dt + \frac{\partial U}{\partial S} dS + \frac{\partial U}{\partial V_t} dV_t +$$
$$[U(JS,t) - U(S,t)]dq$$
$$= \left\{rU - rS\frac{\partial U}{\partial S} - \left[k\left(\overline{V} - V_t\right) - \lambda\right]\frac{\partial U}{\partial V_t} - \lambda E[U(JS,t) - U(S,t)] + \lambda S E(J-1)\frac{\partial U}{\partial S}\right\} dt +$$
$$\frac{\partial U}{\partial S} dS + \frac{\partial U}{\partial V_t} dV_t + [U(JS,t) - U(S,t)]dq \tag{C.8}$$

$$\therefore dU = rU dt + \frac{\partial U}{\partial S}[dS - rS dt + \lambda S E(J-1)] + \frac{\partial U}{\partial V_t}\left[dV_t - E^Q\left(dV_t\right)\right] + [U(JS,t) - U(S,t)]dq -$$
$$E[U(JS,t) - U(S,t)]\lambda dt \tag{C.9}$$

$$\therefore \frac{dU}{U} = rdt + \frac{S}{U}\frac{\partial U}{\partial S}\left[\frac{dS}{S} - rdt + \lambda E(J-1)\right] + \frac{1}{U}\frac{\partial U}{\partial V_t}\left[dV_t - \mathbb{E}^{\mathbb{Q}}\left(dV_t\right)\right] + \frac{1}{U}\{[U(JS,t) - U(S,t)]dq - E[U(JS,t) - U(S,t)]\lambda dt\} \tag{C.10}$$

Then, we construct the vega-neutral and delta-neutral straddle below:

$$\frac{dSTR}{STR} = rdt + \frac{1}{STR}\{[STR(JS,t) - STR(S,t)]dq - E[STR(JS,t) - STR(S,t)]\lambda dt\} \tag{C.11}$$

If $x = [STR(JS,t) - STR(S,t)]dq$

$$\frac{dSTR}{STR} = rdt + \frac{1}{STR}[x - E(x)] \tag{C.12}$$

where x-E(x) is innovation in x.

D. Kelly et al. (2019) CIV measure

Table D.1: Explain OIV using Kelly et al. (2019) CIV

	Estimate		*t-stat*	*Estimate*		*t-stat*	*N*
Panel A: Investment-grade							
Constant	0.113	***	2.894	0.197	***	5.572	83
CIV	0.613	***	6.637	0.598	***	6.898	
Delta				0.441	***	9.708	
OI				0.000		-0.203	
Maturity				0.000	***	-4.798	
Adj R^2	0.154			0.316			
Panel B: Junk-grade							
Constant	0.122	***	4.681	0.204	***	7.399	252
CIV	0.826	***	11.588	0.831	***	12.462	
Delta				0.580	***	11.449	
OI				0.000	**	-2.199	
Maturity				0.000	***	-5.022	
Adj R^2	0.270			0.423			
Panel C: Full Sample							
Constant	0.120	***	5.486	0.202	***	8.982	335
CIV	0.773	***	13.230	0.774	***	14.108	
Delta				0.546	***	13.675	
OI				0.000	**	-2.191	
Maturity				0.000	***	-6.356	
Adj R^2	0.241			0.397			

Note. This table reports the regression results of CIV on OIV, controlling for other variables such as the delta of the option, open interest, and maturity from our 2002-2014 sample period. Adjusted R^2 is shown for each regression. Panels A, B, and C show the results for the investment-grade firms, only the junk-grade firms, and the full sample firms are used, respectively. N is the total number of firms. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Table D.2: Explain Kelly et al. (2019) CIV using OIV

	Estimate		*t-stat*	*Estimate*		*t-stat*	*N*
Panel A: Investment-grade							
Constant	0.409	***	22.172	0.382	***	20.306	83
OIV	0.152	***	6.082	0.172	***	6.500	
Delta				-0.139	***	-4.557	
OI				0.000		-0.924	
Maturity				0.000	**	2.086	
Adj R^2	0.154			0.245			
Panel B: Junk-grade							
Constant	0.366	***	33.393	0.345	***	26.200	252
OIV	0.160	***	9.399	0.169	***	9.869	
Delta				-0.128	***	-4.932	
OI				0.000	**	2.060	
Maturity				0.000	**	2.084	
Adj R^2	0.270			0.377			
Panel C: Full Sample							
Constant	0.377	***	39.783	0.354	***	32.290	335
OIV	0.158	***	11.123	0.170	***	11.757	
Delta				-0.131	***	-6.252	
OI				0.000		0.892	
Maturity				0.000	***	2.683	
Adj R^2	0.241			0.344			

Note. This table reports the regression results of OIV on CIV, controlling for other variables such as the delta of the option, open interest, and maturity from our 2002-2014 sample period. Adjusted R^2 is shown for each regression. Panels A, B, and C show the results for the investment-grade firms, only the junk-grade firms, and the full sample firms are used, respectively. N is the number of firms. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Table D.3: CDS trading Strategy Performance of Kelly et al. (2019) CIV-5

	Quintile portfolios								
	1	2	3	4	5	P	N	1-5	N-P
Annualized	0.185	0.068	-0.084	-0.142	-0.356	-0.308	0.084	0.541	0.396
Cumulative	2.315	0.855	-1.051	-1.782	-4.467	-3.856	1.052	6.782	4.953
Sharpe Ratio	0.492	0.141	-0.320	-0.500	-1.218	-0.996	0.198	2.784	1.847
S.D.	0.334	0.342	0.324	0.324	0.309	0.330	0.323	0.187	0.204
Max. Drawdown	0.674	0.730	0.813	0.912	0.990	0.980	0.700	0.131	0.176

Note. This table reports the trading performance for each quintile from our 2002-2014 sample period. Two long-short strategies are compared with other quintiles. Trading starts from April 2002 to December 2014, without accounting for transaction costs.