Volatility Information Difference between CDS and Option markets and the Cross Section of Option Returns

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Abstract

We examine the information content difference between credit and option markets by extracting volatilities from corporate CDSs (credit default swap) and equity options. The difference is positively related to future option returns. We rank firms based on the normalized volatility spread and analyze the returns for straddle portfolios. A zero-cost trading strategy that long (short) in the portfolio with the largest (smallest) spread generates a significant average monthly return, even after controlling for stock characteristics, traditional risk factors, and moderate transaction costs.

JEL classification: C11, C12, C13, G11, G12.
Keywords: implied volatility; CDS; equity returns; equity option

1. Introduction

A credit default swap (CDS) 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 is an option contract giving the buyer the right to sell a specified amount of an underlying security at a strike price within a specified time, if the underlying price decreases enough below the strike. Corporate CDS and deep out-of-money equity put options are related because they both protect investors against downside risk. Numerous studies examine the information contents between these two markets, for example, Cao, Yu, and Zhong (2010) find that put option implied volatility is a determinant of CDS spreads. Carr and Wu (2007, 2010a) propose a joint valuation framework to estimate option prices and CDS spreads based on their covariation. Carr and Wu (2010b) further develop a link to infer the value of a unit recovery claim (URC) from put and CDS spread and find that the two markets show strong co-movements with similar URC magnitudes. Nevertheless, many studies find the two assets are not mutually replaceable in that both contain information not being fully captured by the other. Guo (2016) link the two markets by extracting volatilities from their prices and provides evidence that CIV (CDS implied volatility) and OIV (option implied volatility) are complementary; Kelly, Manzo and Palhares (2017) argue that CIV differs from OIV because the strike price of CDS is single at a firm's default boundary, which is far deeper out-of-money than a firm's equity puts and thus, CIV and OIV provide different regions of the risk-neutral asset distribution. The differences of information content between CDS and option markets could be a new source of information for option pricing.

In another aspect, volatility is one of the most important determinants of option pricing. Volatility mispricing is commonly found in literature, especially for individual options (Goyal and Saretto, 2009), in which the authors investigate the stock option returns by sorting stocks on the difference between historical realized volatility and at-the-money implied volatility. The future volatility of a firm will be close to its long-run historical volatility, considering the mean-reversion feature of volatility, and thus, large difference between realized volatility and implied volatility suggests option mispricing. Previous studies have found that CIV and OIV are related while with difference, in addition, Guo (2016) shows evidence that CIV is a more efficient future realized volatility predictor than OIV. Therefore, we argue that that a large deviation of OIV from CIV is indicative of option mispricing, from a cross market perspective.

Motivated by the arguments, in this study we examine how volatility information differences between CDS and option markets relate to option pricing. In particular, we provide evidence that the normalized spread between the CIV and OIV can forecast the option straddle returns in the cross section, even after controlling for various firm characteristics and traditional risk factors. A straddle is an options strategy that involves buying both a put and a call option for the underlying security with the same strike price and the same expiration date. A trader profits from a long straddle when the underlying's volatility rises, regardless of the price of the underlying. Therefore, straddle is an ideal financial instrument to study volatility mispricing. Following Goyal and Saretto (2009), we choose to study the option straddle returns since we are interested into the implications of relative volatility difference implied from credit and option markets on subsequent option volatilities.

To measure the spread, we use the weekly five-year CDS contract with modified restructuring (MR) and select the deeply out-of-money put with absolute delta less than 15% with the longest maturity and highest trading volume, this match procedure alleviates the concern of liquidity risk. We then estimate the implied volatilities for CIV following Kelly, Manzo and Palhares (2017) and for OIV, and normalize the volatility difference, named Z-score, between CIV and OIV. We sort stock straddle options into 5 quintiles equal-weighted portfolios and construct a zero-cost trading strategy that long (short) in the portfolio with the largest (smallest) Z-score of firms, the strategy generates a significant average raw monthly return at 6.96% with t-statistics of 2.89. Another zero-cost strategy that long (short) in the portfolio with positive (negative) Z-score produces raw monthly return at 4.75% with t-statistics of 2.90.

These findings hold when we estimate alternative definitions of the CIV and OIV by using the Nelson-Siegel model, alleviating the concern that our results are driven by the chosen CDS and option maturities. We run a panel regression of straddle returns on Z-score controlling for usual stock risk characteristics, such as credit rating, size, book-to-market ratio, momentum, etc. Skewness and kurtosis have predictive power on straddle return, but with small magnitude, and Z-score is robustly significant in all regressions. Double sorts on firm characteristics further confirm our findings that the abnormal returns cannot be fully explained by stock characteristics. We compute the alphas of the long-short straddle portfolios using the Fama-French three-factor model, the Carhart four-factor factor, and the excess return of zero-beta ATM S&P 500 index systematic straddle factor by Coval and Shumway (2001). The alphas are all significant and slightly larger than the raw returns, with an only significant coefficient for the market factor.

Previous literature finds huge impacts from transaction cost on option trading strategies. Due to the market friction, some trading strategies seems profitable but not. To test the impact of market friction, we investigate whether the abnormal returns still exist by adding effective-to-quoted spread ratios to our straddle strategy. De Fontnouvelle, Fisher, and Harris (2003), and Mayhew (2002)) report that the effective-to-quoted spread ratio is lower than 50%, we find both the raw returns and alphas become weaker with larger effective-to-quoted spread ratios. Nevertheless, they are still significant when the ratio is at 25% or less. In addition, returns are more significant for less liquid options.

We discuss two possible explanations for these outstanding performances of Z-score. First, the pair of CIV and OIV exhibits strong mean-reversion characteristics. A low (high) Z-score indicates a subsequent decrease (increase) of option implied volatility, therefore, a strategy that long (short) in the straddle portfolio with the largest (smallest) score could generate a significant average return. We find CIV and OIV are co-integrated among 390 companies (88.84%) in our sample, this relationship suggests a temporal deviation and a relatively mispriced option volatility tends to reverse, and vice versa. On average, the half-life of the decay is equal to 1.2 months, which measures the expected time it takes for the CIV-OIV spread to revert to half of its initial deviation from the mean. Second, the spread constitutes a term premium component that possesses predictability, as we use five-year CDS and short-term (near one month) option for the main analysis. For example, Han, Subrahmanyam, and Zhou (2017) find the slope of CDS term structure (five-year minus one-year CDS spread) predicts future stock returns; Vasquez (2017) shows the slope of the implied volatility term structure (six-month minus five-week volatility on average) is related to future option returns. We are unable to solve the term mismatch between CDS and option, as the shortest CDS in our sample has a constant one-year maturity. Our conclusion remains in the robustness tests by fitting the Nelsen-Siegel model with variable maturities and re-running all tests, indicating that term premium is unlikely to be a major interpretation.

Overall, our article is one of the first to document that the volatility spread between CDS and option has a strong significant relation with subsequent option straddle returns. Previous studies on the option return predictability focus on option and stock markets. For example, Cao and Han (2013) find that idiosyncratic volatility is a determinant of delta-hedged option returns; Bali and Murray (2013) examine the role of risk-neutral skewness on the cross section of option portfolio returns; Goyal and Saretto (2009) show the difference between stock realized volatility and at-the-money option implied volatility predicts option returns. Our paper contributes to the literature by extending their work to credit market.

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

2. Methodology

In this section we briefly present the methodology to extract CIV from CDS spreads, we also introduce the Nelsen-Siegel model for later robustness tests.

2.1 CDS implied volatility

We follow the method of Kelly, Manzo and Palhares (2016) to calculate the CIV. The main idea is that the risk premium in a firm's debt is approximated by its CDS spread, people can then combine the

Merton model (1974) to invert the formula to obtain the CIV σ_A.

$$s(\sigma_A, \mathrm{L}, \mathrm{T}-\mathrm{t}, \mathrm{r}) = -\frac{1}{T-t}\ln(N(d_2) + \frac{N(-d_1)}{L}) \quad (1)$$

$$d_1 = \frac{-\ln(L)}{\sigma_A\sqrt{T-t}} + \frac{1}{2}\sigma_A\sqrt{T-t}\,, d_2 = d_1 - \sigma_A\sqrt{T-t} \quad (2)$$

In the above two formulas, s is a firm's CDS spread, L is the leverage which is a firm's debt divided by its total asset, where debt is the sum of long and short maturity debts, T-t is the time to expiration of CDS, N(*) is the cumulative density function of standard normal distribution.

2.2 The extension of Nelson-Siegel Model on implied volatility term structure

Nelson-Siegel model proposes an excellent parametric method in modeling interest rate term structure (Nelson, 1987). After that, Stein (1989) and Park (2011) propose a two-factor volatility term structure model based on the Nelson-Siegel model. Nevertheless, their model fails to explain the humps shape existing in implied volatility term structure. Guo, Han and Zhao (2014) propose a three-factor parametric volatility term structure model to amplify the more realistic features. Their model contains two mean-reversion processes for both the instantaneous implied volatility and mid-term implied volatility. In this model, the instantaneous implied volatility (σ_t) is assumed to have a mean-reverting feature with the mid-term implied volatility ($\overline{\sigma_t}$), while the mid-term implied volatility is mean reverting to the long-term implied volatility ($\overline{\overline{\sigma}}_t$).

$$\mathrm{d}\sigma_t = -\alpha(\sigma_t - \overline{\sigma}_t)\,dt + \beta\sigma_t\varepsilon\sqrt{dt} \quad (3)$$

$$\mathrm{d}\overline{\sigma}_t = -\kappa(\overline{\sigma}_t - \overline{\overline{\sigma}}_t)\,dt + \xi\overline{\sigma}_t\varepsilon\sqrt{dt} \quad (4)$$

Where the parameters α and κ control the mean-reverting speed, and β and ξ are for volatility diffusion magnitude. Under the model setting of (3) and (4), the expected value of instantaneous volatility at t+j conditional on information at t can be obtained as $\rho = \mathrm{e}^{-\alpha}$ $and\ \tau = e^{-k}$

$$E_t(\sigma_{t+j}) = \mathrm{E}(\overline{\sigma}_{t+j}) + \rho^j[\sigma_t + E(\overline{\sigma}_{t+j})] \quad (5)$$

$$E_t(\overline{\sigma}_{t+j}) = \overline{\overline{\sigma}}_t + \tau^j(\overline{\sigma}_t - \overline{\overline{\sigma}}_t) \quad (6)$$

After integrating the instantaneous implied volatility from t to T, the implied volatility between t and T can be obtained as $IV_t(T)$

$$IV_t(T) = \frac{1}{T}\int_{j=0}^{T}[\overline{\overline{\sigma}}_t + \rho^j(\overline{\sigma}_t - \overline{\overline{\sigma}}_t) + \rho^j\sigma_t - \tau^j(\overline{\sigma}_t - \overline{\overline{\sigma}}_t) - \overline{\overline{\sigma}}_t]dj$$

$$= \overline{\overline{\sigma}}_t + \frac{\rho^T - 1}{T\ln\rho}[\sigma_t - \overline{\overline{\sigma}}_t] - \rho^T(\overline{\sigma}_t - \overline{\overline{\sigma}}_t) \quad (7)$$

In order to simplify the model and avoid overfitting of volatility term structure, $\rho = \mathrm{e}^{-\alpha}$ is used in equation 7

$$IV_t(T) = \beta_{0t} + \beta_{1t}\frac{1-e^{-\alpha\tau}}{\alpha\tau} + \beta_{2t}(\frac{1-e^{-\alpha\tau}}{\alpha T} - e^{-\alpha T}) \quad (8)$$

According to Diebold and Li (2006), we can rewrite equation 8 as the form like the Nelson-Siegel model for implied volatility term structure

$$IV_t(T) = \beta_{0t} + \beta_{1t}\frac{1-e^{-\lambda\tau}}{\lambda\tau} + \beta_{2t}(\frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda T}) \quad (9)$$

Here β_0, β_1 and β_2 represents a long-, short- and medium-term volatility, respectively. We then use this extension of Nelson and Siegel model on CIV term structure, and later run robust tests with the fitted parameters.

3. Data

We obtain the weekly frequency CDS data on 439 US companies from WRDS-Markit between Jan 2002 to Dec 2014. We apply several criteria to select CDS contract, firstly, the selected companies need to have more than one-year CDS data observations, in order to eliminate companies issuing non-frequent CDS. Secondly, the selected CDSs need to have modified restructuring (MR), this criterion is to eliminate the influence of recovery rate on CDS valuation. Then we match the CDS reference list to download the US-firm individual option data from OptionMetrics in WRDS, which includes Greeks, trading volumes, bid price, ask price, implied volatility, etc. Since our purpose is to investigate the information against downside risk, we select those deeply out-of-money put options with positive bid and ask price, trading volume, open interest and implied volatility, with the absolute delta less than 15%[1]. After the above filtering, there are still several put options for one specific date for a same company. To alleviate the concern of liquidity premium and maturity mismatch against CDSs, we choose the puts with the longest maturity and the one with the highest open interest.

Our data contains CDSs for 1-year, 2-year, 3-year, 5-year, 7-year and 10-year maturities, we use 5-year CDSs for our main analysis as they are the most actively traded, and other maturities CDSs for robustness test. In order to obtain a stable holding period for portfolios, we choose the option contracts with maturity near one month and near at-the-money (ATM). In general, the selected call option has a moneyness ranging from 0.975 to 1.025, the corresponding put option is selected with the same strike and maturity time of those of call option. After the expiration of first option contracts, next month option contracts are selected with the same criteria.

The panel A of table 1 lists the summary statistics for CIV, OIV and Z-score. During the 13-year period, the average CIV and OIV are 43.9% and 37.5% respectively. CIV has a lower standard deviation (14.4%) than that of OIV (17.7%). Moreover, the correlation between CIV and OIV is 35.9% on average. In total we have 439 firms with 667 weeks observations.

[Insert Table 1 here]

[1] Note that option returns are computed only for near at-the-money (ATM). We use deeply out-of-money put options only to compute the Z-score.

4. Empirical results

Mean-reverting feature in volatility modelling are widely acknowledged in both academic and industry. Individual stock volatility has an average autocorrelation near 0.7, and the future implied volatility fluctuates around the level of historical volatility (Goyl and Saretto, 2009). This mean-reverting feature also exists between the CIV and OIV (Guo, 2016), which are co-integrated among 390 companies (88.84%) in our sample, that is, the short-maturity option implied volatility likely to move closer to the long-maturity CDS implied volatility. The co-integrated relationship between CIV and OIV indicates a large deviation will not last long and, if option is mispriced, straddle is relatively undervalued when OIV is lower than CIV, and vice versa[2].

4.1 Option Portfolio Formation

Z-score is designed following Guo (2016) and Balvers, Wu and Gilliland (2000). On each date t0, we firstly calculate the series of $\varepsilon_{i,t}$ as $CIV_{i,t} = \beta_i * OIV_{i,t} + \varepsilon_{i,t}, i = [1,2, \dots N]$ for each CDS i, and then the standard deviation σ_i and average mean μ_i of $\varepsilon_{i,t}$ are calculated up to t0, finally we estimate Z-score as $\frac{\varepsilon_{i,t} - \mu_i}{\sigma_i}$.

We calculate the straddle returns for each firm and construct two types of equal-weighted option portfolios by sorting the Z-score of each firm. We group equity options into five portfolios from bottom to top based on the value of Z-score. The bottom (1st) option portfolio has the lowest average Z-score while the top (5th) option portfolio has the highest Z-score. Hence, if volatility mispricing exits and implied volatility follows a mean-reverting process around CIV, the bottom straddle option portfolio will be underpriced while the top straddle option portfolio will be overpriced. We also separate option portfolios into two parts based on the negative and positive Z-score. On average, 88 companies with 90 monthly observations are in each quintile option portfolio, while the negative/positive option portfolio has on average 220 companies with 90 monthly observations.

The panel B of table 1 presents the summary statistics of equal-weighted option portfolios. Patterns of OIV and CIV in quintile portfolios are different. OIV decreases from 0.455 (bottom portfolio) to 0.328 (top portfolio). An adverse pattern exits in CIV, of which it increases from 0.396 (bottom portfolio) to 0.479 (top portfolio). The variation in OIV is higher than that of CIV, as the difference in CIV between top and bottom portfolios is 0.083, while it is 0.127 in OIV. Greeks in selected ATM options are delta, gamma and vega. Delta of call is invariant among either quintile or positive/negative portfolios. Gamma decreases from bottom to top at 0.131 and 0.117 separately, while Vega increases from bottom to top at 5.143 and 6.590 separately.

[Insert Table 1 here]

[2] On average, the half-life of the decay is equal to 1.2 months, which measures the expected time it takes for the spread to revert to half its initial deviation from the mean and determines the optimal holding period for a mean-reverting position.

4.2 Option portfolio returns

Since our interest in this paper is to examine the subsequent straddle returns based only on volatility characteristics, we test the performance of our formed portfolios sorted by the previous Z-scores in this section. Specifically, we hold the grouped portfolios for one month, estimate each group's out-of-sample returns and the long-short neutral portfolio returns.

We select the Wednesday data due to its high liquidity among the weekdays. On each Wednesday, we compute the trading signal (Z-score) and then execute the trading strategies using the closing price at the same day. A straddle return is calculated as the difference between the final payoff and the beginning value, here the beginning value is the sum of the average of bid and ask quote prices of call and put, and the final payoff is max(S-K, K-S). We then compute portfolio returns for each equal weighted quintile or P/N portfolios.

Table 2 reports option portfolios returns sorted by Z-score, including five quintile portfolios and P/N portfolios. 5-1 portfolio is constructed by long the 5th quintile portfolio and short selling the 1st quintile portfolio; P-N portfolio is a combination of a long portfolio with positive Z-score and a short selling portfolio with negative Z-score. Both the five quintile and P/N portfolios show insignificant returns. Nevertheless, the straddle return increases from -2.25% to 4.54% in bottom and top portfolio. The positive straddle portfolio earns a higher return than the negative straddle portfolio at 1.82% and -2.93 respectively. The long-short portfolios show significant and positive returns: the 5-1 straddle has a monthly return at 6.96% with the Newey-West adjusted t-statistics 2.8864, and the P-N straddle has a monthly return at 4.75% with the adjusted t-statistics 2.8979, both are significant at the 1% significance level.

[Insert Table 2 here]

4.3 Controlling for risk and stock characteristics

In this section, we analyze the contribution of option portfolio returns. We follow the method in Goyal and Saretto (2009) by running a multi-factor regression with option returns on traditional stock factors. We investigate whether these traditional stock factors can explain the abnormal return obtained in the last section. Then, we test the option portfolio returns with a double sorting method.

4.3.1 Traditional risk factors

We run a regression of 5-1 and P-N straddle option returns on various risk factors, including the Fama-French three-factor, the Carhart four-factor and the excess return of zero-beta ATM systematic straddle (ZB-STRAD-Rf). We use the excess return of zero-beta ATM S&P 500 straddle index by Coval and Shumway (2001) to control for the systematic straddle risk. We calculate daily ZB-STRAD-Rf and cumulative it into monthly factor.

$$R_{p,t} = \alpha_p + \beta_p * F_t + \varepsilon_{p,t} \quad (10)$$

Where $R_{p,t}$ is the return of a straddle option portfolio and F are for the risk factors. Linear risk-factor model cannot handle and explain all risk premiums in asset pricing (Goyal and Sarreto, 2009). Therefore, this regression is only to test whether the return of straddle option portfolio is related to those systematic risk factors.

Table 3 reports the regression results. The loadings on SMB, HML and MoM are all insignificant at the 10% significance level. Moreover, the loading on ZB-STRAD-Rf is also insignificant for all regressions, indicating our straddle option portfolios sorted by the Z-score is not related to systematic volatility risk. The market factor is the only significant variable and has negative loadings for both the 5-1 and P-N straddle portfolios, as the beta shown in the Table 1 decreases from 1.29 to 1.05 from the 1st to the 5th portfolio, the same for the P-N straddle option portfolios. The alpha is strongly significant at the 1% confidence level and is between 5.10% to 7.90%, which is even larger than the raw return reported in the Table 2, suggesting the incapability of the traditional stock risk factors in explaining our straddle returns.

[Insert Table 3 here]

4.3.2 Stock characteristics

We run a cross-sectional regression of abnormal return on lagged stock characteristics to examine their relationships. The specific model setting follows that in Brennan, Chordia and Subrahmanyam (1998) and Goyal and Sarreto (2009).

$$R_{i,t} - \widehat{\beta_i} * F_t = \alpha_{0,t} + \gamma_{1,t} * Z_{i,t-1} + \epsilon_{i,t} \quad (11)$$

Where $R_{i,t}$ is the return of individual straddle option, and Z are stock characteristics. The $\widehat{\beta_i}$ is obtained by running the multi-factor pricing model with factors F descripted in the section 4.3.1. Z factors include the Z-score and eighteen stock characteristics.

The panel regression results on monthly observations are presented in Table 4. We cluster standard errors by both company and time and control for the year fixed effects. The eighteen stock characteristics include the CDS slope(5-year CDS spread minus 1-year CDS spread), Dummy (Rating over BBB is 1 and others are 0), s.d of civ and s.d of oiv (standard deviation of CIV and OIV in the last month), Beta (beta between the Portfolio 5-1), d(civ) and d(oiv) (changes in the CIV and OIV over last month), Size (log of market capitalization), B/M ratio (Book to market ratio), MoM (the last 6-month cumulative return), Ret(t-1) (the last month stock return), LEV(debt divided by sum of debt and equity), TO (monthly trading volume divided by total common shares outstanding), IVOL(idiosyncratic volatility measured relative to the Fama and French three factor model), Skew(skewness of the last 1 year daily stock log return), and Kurt(kurtosis of the last 1 year daily stock log return), in order to control for the spread term premium in Han, Subrahmanyam, and Zhou (2017), credit rating, systematic risk, momentum, reversal, etc. Among them, the credit rating, size, B/M ratio, MoM, LEV, TO and IVOL show predictive power, both the skewness and kurtosis have predictive power on straddle return but with a small magnitude effect. Z-score remains to be robustly significant in each regression for predicting future straddle returns.

[Insert Table 4 here]

In order to provide a robust result, we conduct a doubt sort on straddle return with Z-score and stock characteristics. Double sort provides a more robust way than a cross-sectional panel regression, due to lack of imposing linear relationship restriction between return and explanatory variables. We first sort options into quintiles based on stock characteristics and, within each quintile, we sort the options in the 1-5 or P/N quintile based on the Z-score.

Table 5 reports the average monthly return for option portfolios and its t-statistics corrected by Newey and West (1987), for eight characteristics that are significant in the Table 4: Size, bm, mom, lev, to, ivol, skew and kurt. Double-sort based on the eight characteristics does not change the return pattern in the quintile straddle portfolios. The 1st quintile portfolio has an average monthly return between -2% and -2.7%, while the 5th quintile portfolio has an average monthly return between 3.5% and 5.4%. Moreover, the 5-1 straddle portfolio has an average return between 5.8% and 7.9%, and, the P-N straddle portfolio has a mean monthly return between 4.6% and 5%. These straddle return performances are similar to the one-way sort based on the Z-score, indicating that these stock characteristics cannot explain all of the abnormal straddle return.

[Insert Table 5 here]

4.4 Robustness tests using the Nelson-Siegel model

In this section, we estimate alternative definitions of the CIV and OIV by using the Nelson-Siegel model, moderating the concern that our results are driven by the chosen CDS and option maturities. We apply the Nelson-Siegel model on the CDS and option implied volatility term structures to obtain parameters and re-run all the tests. In detail, we use the β_0 in equation 9 to replace CIV and OIV, in order to calculate a new Z-score and produce the straddle return.

Table 6 reports the summary statistics for parameters estimated from the Nelson-Siegel model on CDS implied volatility term structure. To fit the model, we use the 1-, 3-, 5-, 7- and 10-year CDSs for the CDS term structure, and the 30-, 60-, 91-, 122-, 152-, 182-, 273-, 365-, 547-, and 730-day maturity options obtained from the volatility surface in OptionMetrics for the option term structure. β_0 for the

CIV term structure is a little higher than that for the OIV term structure but with a lower standard deviation. The average correlation coefficient between them is 0.15, with a standard deviation of 0.366.

[Insert Table 6 here]

Figure 1 plots the time series of estimated parameters averaged among 413 companies. β_0 for CIV is more fluctuated than that in CIV. During the 2008 financial crisis period, both the β_0 for CIV and OIV term structure increase a lot, with the peak time around the beginning of the year 2009.

[Insert Figure 1 here]

Table 7 presents the returns of the option portfolios constructed by using the Z-score based on β_0. The results in table 7 show a similar pattern as in the table 2. Specifically, the quintile straddle portfolios have an increasing pattern from bottom to top, ranging from -6.1% to 1.6% per month. The 5-1 straddle return is 7.8% per month, and the P-N straddle portfolio return is 6.2%. The performance in the 5-1 or P-N straddle portfolios is a little higher than previous portfolios in the Table 2.

[Insert Table 7 here]

In summary, our conclusion remains in the robustness tests by fitting a Nelsen-Siegel model with variable maturities and re-running all tests, indicating that the abnormal straddle returns formed by Z-score is unlikely driven by a certain maturity, and the term premium is unlikely to be a major interpretation.

4.5 Transaction costs: bid-ask spreads

In the above tests, we use mid-price as the trading price, however, in reality, we can only buy an asset at the ask price and sell it at the bid price. Literature shows evidence that the real bid-ask spread is smaller than quoted bid-ask spread but still at a high level (De Fontnouvelle et al, 2003; Mayhew, 2002; Goyal and Saretto, 2009). In this section we follow the process of Goyal and Saretto (2009) and consider the 25%, 50%, 75%, 100% of quoted bid-ask spread in trading straddles.

We also group option portfolio by liquidity for the concern about liquidity risk, we compute two measures to access liquidity. The first measure is the average bid-ask spread of all options traded in previous month for the firm, and the second measure is the average daily trading volume of options traded in previous month for the firm. We first sort options into quintile portfolio based on the Z-score; then, in each quintile straddle portfolio, we sort options into two portfolios with low and high liquidity. The returns of 5-1 and P-N portfolios are finally computed for each subgroup.

Table 8 reports the long-short portfolios under different efficient bid-ask spreads. Transaction costs deteriorate the performance of the long-short strategy. Without transaction cost, the 5-1 portfolio earns 6.96% monthly raw return, while it decreases dramatically to -4.5% per month under 100% efficient bid-ask spread condition. The P-N portfolios face the same situations on raw return, from 4.7% per month to -6.5% per month. De Fontnouvelle, Fisher, and Harris (2003), and Mayhew (2002)) report that the effective-to-quoted spread ratio is lower than 50%. It is interesting to note that, under the 25% quoted bid-ask spread condition, both the alpha and raw return in the 5-1 or P-N portfolios are positive and significant at the 10% significance level. Raw returns and alphas are 4.2% and 4.8% for the 5-1 portfolio and 2% and 2.3% for the P-N portfolio, respectively.

Option liquidity also influences the performance of the long-short strategy. The low liquidity portfolio performs better than the high liquidity portfolio. For the 5-1 portfolios, the return of the low liquidity portfolio decreases from 10.3% to 0.2%, but is still significant at the 5% significance level under the 50% quoted spread condition with a monthly return at 5.4%; while the return of the high liquidity portfolio decreases from 3.8% to -9.6%. For the P-N portfolios, the low liquidity portfolio decreases from 7.5% to -2.3%, but is significant at 1% under the 25% quoted spread at a monthly return of 5.1%; while the high liquidity portfolio decreases dramatically from 2.5% to -10.8%. Another measure of liquidity based on the average trading volume of options exhibits similar patterns.

We conclude that transaction cost dramatically decreases the trading performance of this long-short strategy. Both the raw returns and alphas become weaker with larger effective-to-quoted spread ratios. Nevertheless, they are still significant when the ratio is at 25% or less. In addition, returns are more significant for less liquid options.

[Insert Table 8 here]

4.6 Subsample analysis around the Great recession

In this section we conduct a robustness test using sample periods around the Great recession, in particular, we compute the option straddle portfolio returns during the year 2007-2009, in order to examine whether our results are driven by certain turbulent years. Table 9 reports the option portfolios returns sorted by Z-score, the straddle return increases from -1.31% to 9.15% in bottom and top portfolio. The positive straddle portfolio earns a higher return than the negative straddle portfolio at 8.13% and 2.13% respectively. Both the long-short 5-1 and P-N portfolios show significant return at the 10% significant level. Compared with the results for the whole sample in Table 2, the straddle returns become large but less significant, due to the volatile market and hence the increasing standard deviation of sorted portfolio returns, nevertheless, our finding remains.

[Insert Table 9 here]

5. Conclusion

We document a positive relation between the Z-score and straddle returns in the cross section, where

Z-score is computed as the normalized spread between the CDS and option implied volatilities. We rank stocks according to the Z-score and investigate the subsequent one-month straddle returns. We sort straddle options into 5 quintiles equal-weighted portfolios and construct a zero-cost trading strategy that long (short) in the portfolio with the largest (smallest) Z-score of firms, the strategy generates a significant average raw monthly return at 6.96% with t-statistics of 2.89.

The abnormal returns sorting by Z-score cannot be fully explained by traditional stock risk factors, nor by stock characteristics. The alphas of the long-short straddle portfolios using the Fama-French three-factor model, the Carhart four-factor factor, and the excess return of zero-beta ATM S&P 500 index systematic straddle factor by Coval and Shumway (2001) remain strongly significant. Double sorts confirm the predictive power of the Z-score and the returns hold for alternative definitions of Z-score. Transaction costs reduce the profits; nevertheless, they are still significant when the effective-to-quoted spread ratio is at 25% or less, especially for less liquid options. Our results are important to option market traders, who should consider the information content of CDS market when making investment decisions.

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Table 1 Summary Statistics of data and option portfolios sorted by Z-score

Panel A presents the summary statistics about mean, standard deviation, 10% percentile, 90% percentile, maximum and minimum of CIV, OIV, option maturity, equity, debt, risk free rate, CDS spread(s), correlation coefficients, and option delta. Sample contains 439 companies from Jan 2002 to Dec 2014. Panel B reports the statistics of sorted option portfolios. Portfolios 1 to 5 are obtained by sorting Z-score from bottom to top and equal-weighted. Portfolios N and P are obtained by sorting by the sign of Z-score. Δ, Γ and Υ is the delta, gamma and vega, respectively. The sample includes 439 companies and 168646 pairs of call and put. Period begins with 2002 to 2014.

Panel A: Data summary

Variables	Mean	S.D.	Min	0.25	Median	0.75	Max	Total
# of Firms								439
# of Weeks								667
# of Observations	384.68	206.17	52	192	399	589	667	
Maturity(day)	308.46	261.32	2	80	206	535	969	
E(Millions)	27527.31	47261.01	62.46	4931.34	12152.99	27317.19	525785.64	
D(Millions)	14338.08	63195.21	0.21	1451.90	3532.00	8224.00	916322.00	
r(%)	1.71	1.77	0.09	0.19	1.06	3.16	5.30	
s(%)	1.52	2.41	0.02	0.39	0.75	1.67	139.39	
CIV(%)	43.90	14.42	5.17	35.29	42.83	50.58	295.90	
OIV(%)	37.54	17.70	3.10	25.94	33.35	43.92	240.14	
cor(s,CIV)	47.78	37.70	-54.49	22.60	54.69	79.80	99.76	
cor(CIV,OIV)	25.91	38.02	-87.49	3.07	31.54	52.87	93.60	
Put's delta	-0.10	0.04	-0.15	-0.13	-0.10	-0.07	0.00	

Panel B: Option portfolios

	1	2	3	4	5	P	N
Z-score	-1.051	-0.338	0.019	0.373	0.952	0.646	-0.667
CIV	0.396	0.402	0.417	0.436	0.479	0.45	0.398
OIV	0.455	0.386	0.357	0.343	0.328	0.342	0.413
d.civ	-0.004	-0.002	0	0.001	0.003	0.002	-0.002
d.oiv	0.033	0.002	-0.006	-0.012	-0.021	-0.015	0.014
Δ	0.506	0.504	0.504	0.505	0.506	0.506	0.505
Γ	0.131	0.125	0.122	0.118	0.117	0.12	0.128
Υ	5.143	5.598	5.976	6.396	6.59	6.347	5.369

Table 2 Returns of option portfolios sorted by Z-score

Option price is calculated as the average of closing bid and closing ask price. The terminal payoff of call option is max(S_T-K, 0) while that of put option is max(K-S_T, 0). K is the strike price and S_T is the stock price at maturity time. The Straddle portfolios are equal-weighted. T-statistics is corrected by the Newey and West (1987). The sample includes 439 companies and 168646 pairs of call and put. Period begins with 2002 to 2014.

	Straddle Returns								
	1(low)	2	3	4	5(high)	P	N	5-1	P - N
mean	-0.0225	-0.0212	-0.0327	0.0029	0.0454	0.0182	-0.0293	0.0696***	0.0475***
t-value	-0.9840	-0.8109	-1.2636	0.1093	1.4066	0.6902	-1.1875	2.8864	2.8979
p-value	0.3255	0.4177	0.2068	0.9130	0.1600	0.4903	0.2355	0.0040	0.0039

Table 3 Risk-adjusted option return

This table presents the regression results of returns the portfolio 5-1 and portfolio P-N: $R_{p,t} = \alpha_p + \beta_p * F_t + \varepsilon_{p,t}$ The risk factors include the Fama and French(1993) three factors (MKT-Rf, SMB, HML), Carhart(1994) momentum factor(MoM), and the Covol and Shumway(2001) excess zero-beta S&P 500 straddle factor (ZB-STRAD-Rf). The first row is for the regression coefficients and the second row is the corresponding t-statistics corrected by the Newey and West(1987).

	Straddles			
	5-1		P-N	
	(1)	(2)	(3)	(4)
Alpha	0.079***	0.076***	0.052***	0.051***
	3.210	3.082	3.424	3.130
MKT-Rf	-1.461***	-1.231**	-0.719	-0.584
	-2.992	-2.226	-1.638	-1.166
SMB		1.361		0.899
		1.593		1.337
HML		-0.346		-0.787
		-0.456		-1.157
MoM		0.550		0.114
		1.292		0.277
ZB-STRAD-Rf	0.031	0.060	0.012	0.028
	0.382	0.821	0.201	0.501
Adj R^2	0.030	0.039	0.011	0.018

Table 4 Individual option returns controlling for stock characteristics (Cross-sectional regressions)

We estimate the following cross-sectional regression for individual option returns:
$R_{i,t} - \widehat{\beta_i} * F_t = \alpha_{0,t} + \gamma_{1,t} * Z_{i,t-1} + \epsilon_{i,t}$ Where F are the Fama and French(1993) three factors (MKT-Rf, SMB, HML), the Carhart(1994) momentum factor(MoM), and the Covol and Shumway(2001) excess zero-beta S&P 500 straddle factor (ZB-STRAD-Rf). The characteristics include Z-score, CDS slope(5-year CDS spread minus 1-year CDS spread), Dummy (Rating over BBB is 1 and others are 0), s.d of civ and s.d of oiv (standard deviation of CIV and OIV in last month), Beta (beta between Portfolio 5-1), d(civ) and d(oiv) (changes in CIV and OIV over last month), Size (log of market capitalization), B/M ratio (Book to market ratio), MoM (last 6-month cumulative return), Ret(t-1) (last month stock return), LEV(debt divided by sum of debt and equity), TO (monthly trading volume divided by total common shares outstanding), IVOL(idiosyncratic volatility measured relative to the Fama and French three factor model), Skew(skewness of last 1 year daily stock log return), and Kurt(kurtosis of last 1 year daily stock log return). The last row shows the adjusted R^2. All regressions include the year fixed effects and cluster the standard errors by firm and month.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Z-score	0.021***	0.019***	0.039***	0.039***	0.052***	0.039***	0.040***	0.040***	0.042***	0.045***	0.051***	0.049***	0.050***	0.049***
	2.798	2.491	4.683	4.613	7.117	4.732	5.062	4.718	4.822	4.918	6.708	6.322	5.891	6.558
CDS slope		0.878												
		0.837												
Dummy			0.042***											
			4.490											
civ				0.021										
				0.524										
oiv					0.115***									
					2.626									
s.d of civ						-0.024								
						-0.116								
s.d of oiv							0.032							
							0.459							
Beta								-0.472						
								-0.929						
d(civ)									-0.032			-0.208		
									-0.175			-0.975		
d(oiv)										0.131			0.099	
										1.449			1.078	
Size, log(VE)											0.015***	0.013***	0.012***	0.015***
											2.841	2.405	2.347	2.797

B/M ratio											0.295***	0.219***	0.219***	0.294***
											6.665	5.297	5.293	6.741
MoM											0.069***	0.065***	0.066***	0.078***
											3.938	3.880	3.960	4.326
Ret(t-1)											0.082	-0.023	-0.010	0.100*
											1.504	-0.356	-0.161	1.839
LEV											-0.169***	-0.158***	-0.156***	-0.161***
											-3.870	-3.863	-3.825	-3.826
TO											0.410***	0.459***	0.457***	0.426***
											9.314	10.215	10.208	9.737
IVOL											-0.760***	-0.785***	-0.792***	-0.796***
											-7.321	-7.907	-8.031	-7.533
Skew														-0.034***
														-4.785
Kurt														0.004***
														3.480
Adj R^2	0.000	0.000	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.026	0.021	0.022	0.028

Table 5 Option Portfolio returns controlling for stock characteristics (double-sort)

We first sort options into quintiles based on stock characteristics and, within each quintile, we sort the options in the 1-5 or P/N portfolios based on Z-score. This table reports the average monthly return and its t-statistics corrected by the Newey and West (1987).

Quintile Portfolio: Straddle Returns

Control	1	2	3	4	5	P	N	5-1	P-N
size	-0.023	-0.024	-0.021	0.011	0.035	0.022	-0.028	0.059	0.050
	-0.982	-0.896	-0.769	0.363	1.124	0.790	-1.129	2.672	2.999
bm	-0.025	-0.001	-0.024	0.004	0.035	0.024	-0.022	0.060	0.046
	-1.031	-0.020	-0.918	0.147	1.108	0.918	-0.887	2.486	2.598
mom	-0.027	-0.031	-0.018	-0.010	0.037	0.014	-0.032	0.064	0.047
	-1.209	-1.293	-0.680	-0.406	1.203	0.558	-1.364	2.632	2.854
lev	-0.022	-0.014	-0.010	-0.010	0.041	0.021	-0.028	0.063	0.049
	-0.898	-0.541	-0.402	-0.356	1.269	0.781	-1.125	2.620	2.981
to	-0.026	-0.031	-0.017	-0.004	0.054	0.021	-0.027	0.079	0.048
	-1.020	-1.306	-0.657	-0.141	1.631	0.780	-1.088	3.276	2.876
ivol	-0.026	-0.010	-0.020	-0.006	0.039	0.022	-0.028	0.065	0.050
	-1.101	-0.360	-0.754	-0.229	1.192	0.813	-1.138	2.643	3.014
skew	-0.024	-0.016	-0.025	0.002	0.036	0.020	-0.028	0.060	0.048
	-1.017	-0.619	-0.861	0.092	1.115	0.748	-1.125	2.512	2.916
kurt	-0.020	-0.024	-0.014	-0.005	0.038	0.021	-0.028	0.058	0.049
	-0.893	-0.894	-0.520	-0.165	1.192	0.758	-1.138	2.459	2.938

Table 6 Summary Statistics for parameters in the Nelsen-Siegel model

	mean	st.d	0.25	0.75	max	min	median	Total
# of company								413
# of week								666
observation.civ	361	209	169	565	666	8	370	
observation.oiv	387	203	199	586.5	666	52	405	
civ.b0	0.356	0.119	0.290	0.404	5.968	0.000	0.345	
civ.b1	0.524	0.299	0.378	0.686	15.040	-4.317	0.537	
civ.b2	-0.132	0.387	-0.199	0.001	5.855	-25.551	-0.005	
oiv.b0	0.313	0.131	0.229	0.364	3.342	-0.031	0.284	
oiv.b1	0.017	0.112	-0.044	0.051	2.900	-1.690	-0.003	
oiv.b2	0.004	0.175	-0.073	0.077	7.215	-5.498	0.000	
cor(civ,oiv).b0	0.150	0.366	-0.098	0.395	0.943	-0.929	0.200	
cor(civ,oiv).b1	-0.041	0.205	-0.171	0.083	0.681	-0.646	-0.034	
cor(civ,oiv).b2	0.038	0.129	-0.028	0.119	0.457	-0.628	0.037	

Table 7 Returns of option portfolios sorted by Z-score (the Nelsen-Siegel model)

All option portfolio construction follows the Table 3. T-statistics is corrected by the Newey and West(1987).

Straddle Returns

	1(low)	2	3	4	5(high)	P	N	5-1	P - N
mean	-0.061***	-0.026	-0.034	-0.006	0.016	0.017	-0.044*	0.078***	0.062***
t-value	-2.547	-1.001	-1.210	-0.241	0.587	0.671	-1.739	3.934	4.032
p-value	0.011	0.317	0.227	0.810	0.557	0.503	0.083	0.000	0.000

Table 8 Impact of Liquidity and transaction costs

Option portfolios are sorted into two groups based on option liquidity. Average bid-ask spread means the average bid-ask spread of all the options traded in the last month of a firm; average trading volume means the average of the daily option trading volume of the firm. MidP is the price at the middle of bid and ask; ESPR is the effective spread while QSPR is the quoted spread. The first row is the average return and the second row is its t-statistics.

	5-1					P-N				
			ESPR/QSPR					ESPR/QSPR		
	MidP	25%	50%	75%	100%	MidP	25%	50%	75%	100%
All	0.070***	0.042***	0.012	-0.015	-0.045***	0.047***	0.020*	-0.010	-0.036***	-0.065***
	4.867	2.925	0.798	-1.081	-3.116	4.508	1.888	-0.872	-3.370	-5.960
Alpha	0.076***	0.048***	0.017	-0.010	-0.040***	0.051***	0.023**	-0.007	-0.034***	-0.063***
	5.434	3.420	1.214	-0.720	-2.833	4.834	2.158	-0.654	-3.186	-5.809
Based on average bid-ask spread of options										
Small	0.038**	0.006	-0.032	-0.059***	-0.096***	0.025*	-0.006	-0.045***	-0.072***	-0.108***
	1.967	0.323	-1.518	-2.948	-4.650	1.724	-0.431	-2.599	-4.493	-6.332
Large	0.103***	0.079***	0.054**	0.029	0.002	0.075***	0.051***	0.027	0.002	-0.023
	4.271	3.280	2.267	1.221	0.103	4.330	2.957	1.567	0.146	-1.355
Based on average trading volume of options										
Low	0.094***	0.061***	0.024	-0.004	-0.041*	0.067***	0.035**	0.000	-0.028*	-0.061***
	3.859	2.551	0.979	-0.178	-1.684	4.094	2.189	-0.004	-1.754	-3.836
High	0.050***	0.028	0.006	-0.017	-0.042**	0.036**	0.013	-0.011	-0.036*	-0.064***
	2.578	1.440	0.289	-0.886	-2.113	2.085	0.714	-0.620	-1.895	-3.078

Table 9 Straddle returns during the 2008 financial crisis period

Option price is calculated as the average of closing bid and closing ask price. The terminal payoff of call option is max(S_T-K, 0) while that of put option is max(K-S_T, 0). K is the strike price and S_T is the stock price at maturity time. The Straddle portfolios are equal-weighted. T-statistics is corrected by the Newey and West (1987). The sample period is from 2007 to 2009.

	1(low)	2	3	4	5(high)	P	N	5-1	P-N
mean	-0.0131	0.0250	0.0558	0.1048	0.0915	0.0813	0.0213	0.1046*	0.0600*
t-value	-0.1536	0.2382	0.5300	1.0099	0.7295	0.7257	0.2059	1.7847	1.7206
p-value	0.8783	0.8123	0.5974	0.3152	0.4675	0.4698	0.8373	0.0776	0.0887

Figure1. Time series of parameters fitting by the Nelsen-Siegel model in CIV and OIV term structure.

The first one is for CIV, the second one is for OIV and the last one shows the changes for beta0 of CIV and OIV between 2002 and 2014.