No. 2005 [EN]

IMI Working Paper

Volatility Information Difference between CDS, Options, and the Cross Section of Options Returns

Biao Guo, Yukun Shi and Yaofei Xu

INTERNATIONAL MONETARY INSTITUTE

IMI Working Paper No. 2005 [EN]

Volatility Information Difference between CDS, Options, and the Cross Section of Options Returns

By BIAO GUO, YUKUN SHI, YAOFEI XU[1]

Abstract

We examine the difference in the information content in credit and options markets by extracting volatilities from corporate credit default swaps (CDSs) and equity options. The standardized difference in volatility, quantified as the volatility spread, is positively related to future option returns. We rank firms based on the volatility spread and analyze the returns for straddle portfolios buying both a put and a call option for the underlying firm with the same strike price and expiration date. A zero-cost trading strategy that is long (short) in the portfolio with the largest (smallest) spread generates a significant average monthly return, even after controlling for individual stock characteristics, traditional risk factors, and moderate transaction costs.

Keywords: implied volatility; CDS; equity returns; equity option

JEL classification: C11, C12, C13, G11, G12.

[1] Biao Guo, Research Fellow of IMI, is at the School of Finance & China Financial Policy Research Center, Renmin University of China, biao.guo@outlook.com.
Yukun Shi, corresponding author, is at the Accounting and Finance department of Adam Smith Business School, University of Glasgow, Yukun.Shi@glasgow.ac.uk.
Yaofei Xu is at the University of Glasgow, y.xu.2@research.gla.ac.uk. We thank the seminar participants at the 7th International Conference on Futures and Other Derivatives for their insightful comments, all errors are ours.

1. Introduction

A credit default swap (CDS) is a contract in which the buyer, who wishes to protect themselves against the risk of default, 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 CDSs and deep out-of-the-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 method to infer the value of a unit recovery claim (URC) from put and CDS spreads and find that the two markets show strong co-movements with similar URC magnitudes. Nevertheless, many studies find that the two assets are not mutually replaceable because both reflect information and mitigate risks which are not being fully captured by the other. Guo (2016) links the two markets by extracting volatilities from their prices and provides evidence that the CDS implied volatility (CIV) and option implied volatility (OIV) are complementary. Kelly, Manzo and Palhares (2017) argue that CIV differs from OIV because the strike price of a CDS lies at a firm's default boundary, which is far deeper out-of-the-money than a firm's equity puts and thus, CIV and OIV reflect different regions of the risk-neutral asset distribution. Thus, the differences in the information content between CDS and option markets could be a new source of information for option pricing.

In particular, volatility is one of the most important determinants of option pricing. It is commonly exemplified in the literature that volatility is mispriced, especially for individual options. For example, Goyal and Saretto (2009) 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 is expected to 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 that an option is mispriced. Previous studies have found that CIV and OIV are related, but different. Specifically, 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 these 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 asset's volatility rises, regardless of the price of the underlying asset. Therefore, a straddle is an ideal speculation strategy to use to study volatility mispricing. Following Goyal and Saretto (2009), we choose to study the option straddle returns since we are interested in the implications of the relative volatility difference implied from credit and option market prices 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-the-money put with i) absolute delta less than 15%, ii) with the longest maturity and iii) with the 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. Finally, we normalize the volatility difference between CIV and OIV, named the Z-score. We sort stock straddle options into 5 quintiles of equal-weighted portfolios and construct a zero-cost trading strategy that is long (short) in the portfolio with the largest (smallest) Z-score of firms. The strategy generates a significant average raw monthly return of 6.96% with a t-statistic of 2.89. Another zero-cost strategy that is long (short) in the portfolio with a positive (negative) Z-score produces a raw monthly return of 4.75% with a t-statistic of 2.90.

These findings hold when we estimate alternative definitions of the CIV and OIV by using the Nelson-Siegel model, thus 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. Furthermore, we identify that skewness and kurtosis have predictive power for the straddle return, but with a small magnitude, and the Z-score is robustly significant in all regressions. Double sorts on Z-score and 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 model, and the excess return of the zero-beta at-the-money (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. The only significant coefficient is that of the market factor.

Previous literature identifies a huge impact of transaction costs on the profitability of option trading strategies (De Fontnouvelle et al, 2003; Mayhew, 2002; Goyal and Saretto, 2009). Due to the market friction, some trading strategies seems profitable, but others do 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%. In this study, we find that both the raw returns and the 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 the outstanding performance observed based on the Z-score. First, the pair of CIV and OIV values exhibits strong mean-reversion characteristics. A low (high) Z-score is related to a subsequent decrease (increase) of OIV. Therefore, a strategy that is 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 for 390 companies (88.84%) in our sample. This relationship suggests a temporal deviation and a relatively mispriced option volatility tends to reverse. 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 can be predicted using five-year CDS and short-term (near one month) option, as we evidence in the main analysis. This result is similar to that of Han, Subrahmanyam, and Zhou (2017) who find that the slope of the CDS term structure (five-year minus one-year CDS spread) predicts future stock returns. Similarly, Vasquez (2017) shows that the slope of the implied volatility term structure (six-month minus five-week volatility on average) is related to future option returns. Nonetheless, we are unable to solve the term mismatch between CDSs and options, as the shortest CDS in our sample has a constant one-year maturity. Our conclusion is further supported by the robustness tests whereby the Nelsen-Siegel model with variable maturities is fitted and all the tests are re-run. The results indicate that the term premium is unlikely to be a major interpretation of the predictability.

Overall, our article is one of the first to document that the volatility spread between CDSs and options has a strong, significant relationship 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 and Goyal and Saretto (2009) show that the difference between stock realized volatility and at-the-money option implied volatility predicts option returns. Gang, Zhao and Ma (2019) investigates the predictive power of the put-call ratios (PCRs) on the China's 50ETF return. Our paper contributes to the literature by extending the work of these authors to the credit market.

The rest of this study is structured 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 present the methodology to extract the CIV from CDS spreads. We also introduce the Nelsen-Siegel model which is subsequently used for robustness tests.

2.1 CDS implied volatility

We follow the method of Kelly, Manzo and Palhares (2016) to calculate the CIV. Thereby, the risk premium in a firm's debt is approximated by its CDS spread and this can be combined with Merton's (1974) model to invert the formula to obtain the CIV, notated by σ_A.

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

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

In the above two formulas, s is a firm's CDS spread, L is the leverage (i.e. 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 the CDS, and N(*) is the cumulative density function of standard normal distribution.

2.2 The extension of the Nelson-Siegel model based on implied volatility term structure

The Nelson-Siegel model proposes an excellent parametric method for modeling interest rate term structure (Nelson, 1987). Furthermore, 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 hump-shape which can be observed in the implied volatility term structure. Guo, Han and Zhao (2014) propose a three-factor parametric volatility term structure model to account for the features observed in reality. Specifically, 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 respect to the mid-term implied volatility ($\overline{\sigma_t}$), while the mid-term implied volatility is mean reverting with respect to the long-term implied volatility ($\overline{\overline{\sigma_t}}$). This can be captured in formulas as follows:

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

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

Here, 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 time t, can be obtained as $\rho = \mathrm{e}^{-\alpha}\ and\ \tau = e^{-k}$. Furthermore,

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

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

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

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

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

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

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

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

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

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

3. Data

The dataset is comprised of weekly CDS data on 439 US companies from WRDS-Markit between Jan 2002 to Dec 2014. We apply several criteria to select CDS contracts for inclusion in the investigation. Firstly, the selected companies need to have more than one-year of CDS data observations. Thus, companies issuing CDSs on an infrequent basis are excluded. Secondly, the selected CDSs need to have modified restructuring (MR). This criterion is used to eliminate the influence of the 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 all the Greeks, trading volumes, bid price, ask price, implied volatility, etc. Since our purpose is to investigate the information with respect to downside risk, we select deeply out-of-the-money put options with a positive bid and ask price, trading volume, open interest and implied volatility, and with an absolute delta less than 15%[2]. After the above filtering, there are still cases where several put options exist for one specific date for the same company. To alleviate the concern of a liquidity premium and maturity mismatch against CDSs, we choose the puts with the longest maturity and the highest open interest.

Our data contains CDSs with 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 CDSs with other maturities for robustness tests. In order to obtain a stable holding period for portfolios, we choose the option contracts which have a maturity close to one month and which are close to being 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 as those of the call option. After the expiration of the first option contracts, option contracts for the following month are selected with the same criteria.

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. The CIV has a lower standard deviation (14.4%) than that of the OIV (17.7%). Moreover, the correlation between

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

the CIV and OIV is 35.9%, on average. In total, the dataset comprises 439 firms with 667 weeks of observations.

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

4. Empirical results

The mean-reverting feature in volatility modelling is widely acknowledged, both in academic and in industry. Individual stock volatility has an average autocorrelation near 0.7 and the future implied volatility fluctuates around the level of the historical volatility (Goyl and Saretto, 2009). This mean-reverting feature also exists between the CIV and OIV (Guo, 2016), which are co-integrated for 390 companies (88.84%) in our sample. That is, the short-maturity option implied volatility is likely to move closer to the long-maturity CDS implied volatility. The co-integrated relationship between the CIV and OIV indicates a large deviation will not last long and, if an option is mispriced, the straddle is relatively undervalued when the OIV is lower than the CIV, and vice versa[3].

4.1 Option Portfolio Formation

The Z-score is calculated following Guo (2016) and Balvers, Wu and Gilliland (2000). On each date t_0, we firstly calculate the series of $\varepsilon_{i,t}$ as $CIV_{i,t} = \beta_i * OIV_{i,t} + \varepsilon_{i,t}, i = [1,2, \ldots N]$ for each CDS, i. Then, the standard deviation, σ_i , and average mean, μ_i, of $\varepsilon_{i,t}$ are calculated up to t_0. Finally, we estimate the 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-scores of the firms. We group equity options into five portfolios, from bottom to top, based on the value of the 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 exists and implied volatility follows a mean-reverting process around the 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 of option portfolios, while the positive/negative (P/N) option portfolio has on average of 220 companies with 90 monthly observations.

Panel B of Table 1 presents the summary statistics of equal-weighted option portfolios. The patterns of OIV and CIV in the quintile portfolios are different. The OIV decreases from 0.455 (bottom portfolio) to 0.328 (top portfolio). The opposite pattern exists for CIV, whereby 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 the CIV of the top and bottom portfolios is 0.083, while it is 0.127 for the OIV. The Greeks for the selected ATM options are delta, gamma and vega. The delta of the call is invariant among the different quintiles and for P/N portfolios. Gamma decreases from the bottom to top quintiles with values ranging from 0.131 to 0.117, while vega increases from bottom to top, with values ranging from 5.143 to 6.590.

[3] 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. This determines the optimal holding period for a mean-reverting position.

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

4.2 Option portfolio returns

Since our interest in this paper is to examine the subsequent straddle returns based only on volatility characteristics, in this section, we test the performance of our portfolios sorted by the Z-scores as described in the previous section. Specifically, we hold the grouped portfolios for one month and estimate each group's out-of-sample returns as well as 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 on 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 for call and put options and the final payoff is max(S-K, K-S). We then compute portfolio returns for each equal weighted quintile or P/N portfolio.

Table 2 reports the option portfolio returns sorted by Z-score, including the five quintile portfolios and the P/N portfolios. The 5-1 portfolio is constructed by going long on the 5th quintile portfolio and short selling the 1st quintile portfolio. The 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%, spanning from the bottom to top portfolios. The positive straddle portfolio earns a higher return than the negative straddle portfolio at 1.82%, as opposed to the -2.93% for the negative portfolio. The long-short portfolios show significant and positive returns: the 5-1 straddle has a monthly return of 6.96% with a Newey-West adjusted t-statistic of 2.8864. The P-N straddle (positive minus negative portfolio) has a monthly return of 4.75% with an adjusted t-statistic of 2.8979. Both are significant at the 1% significance level.

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

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 on Z-score and firm characteristics.

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 model, the Carhart four-factor model and the excess return of the zero-beta ATM systematic straddle (ZB-STRAD-Rf). We use the excess return of the 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 cumulate it to attain a monthly factor. This can be represented as follows:

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

where $R_{p,t}$ is the return of a straddle option portfolio and F are the risk factors. The linear risk-factor model cannot handle and explain all risk premiums in asset pricing (Goyal and Sarreto, 2009). Therefore, this regression is only used to test whether the return of the straddle option portfolio is related to the 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, are 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, which is evidenced by the beta value shown in Table 1, which decreases from 1.29 to 1.05 from the 1st to the 5th portfolio. A similar observation applies 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 Table 2, which suggests that traditional stock risk factors do not explain our straddle returns.

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

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 of Brennan, Chordia and Subrahmanyam (1998) and Goyal and Sarreto (2009). Specifically, we define

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

where $R_{i,t}$ is the return of the individual straddle option and Z represents the stock characteristics. The $\widehat{\beta_i}$ is obtained by running the multi-factor pricing model with F factors, as described in section 4.3.1. Z factors include the Z-score and 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 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 on straddle returns. Both the skewness and kurtosis also have predictive power on straddle return but with a small magnitude effect. The Z-score continues to be robustly significant for predicting future straddle returns in each regression.

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, the Carhart (1994) momentum factor, and the Covol and Shumway (2001) excess zero-beta S&P 500 straddle factor. 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

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 into the 1-5 or P/N quintile based on the Z-score.

Table 5 reports the average monthly return for option portfolios and the respective t-statistics corrected by the Newey and West (1987) method for eight characteristics that are significant in Table 4: Size, B/M, MoM, LEV, TO, IVOL, Skew and Kurt. Conducting the 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 results are similar to the results based on the one-way sort using the Z-score, thus providing further evidence that these stock characteristics cannot explain all of the abnormal straddle return.

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

4.4 Robustness tests using the Nelson-Siegel model

In this section, we estimate the CIV and OIV using alternative definitions as per the Nelson-Siegel model. This serves to mitigate concerns 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 the parameters and re-run all the tests. Specifically, we use the value for β_0 from equation 9 to replace CIV and OIV, and then calculate a new Z-score and produce the straddle return.

Table 6 reports the summary statistics for the parameters estimated using the Nelson-Siegel model for the 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 slightly higher than that for the OIV term structure but has a lower standard deviation. The average correlation coefficient between them is 0.15, with a standard deviation of 0.366.

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	

Figure 1 plots the time series of estimated parameters when values are averaged for the 413 companies in the sample. β_0 for CIV fluctuates more than in the original CIV value. In particular, during the 2008 financial crisis period, both the β_0 for CIV and the OIV term structure increase significantly, with the peak time around the beginning of the year 2009.

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.

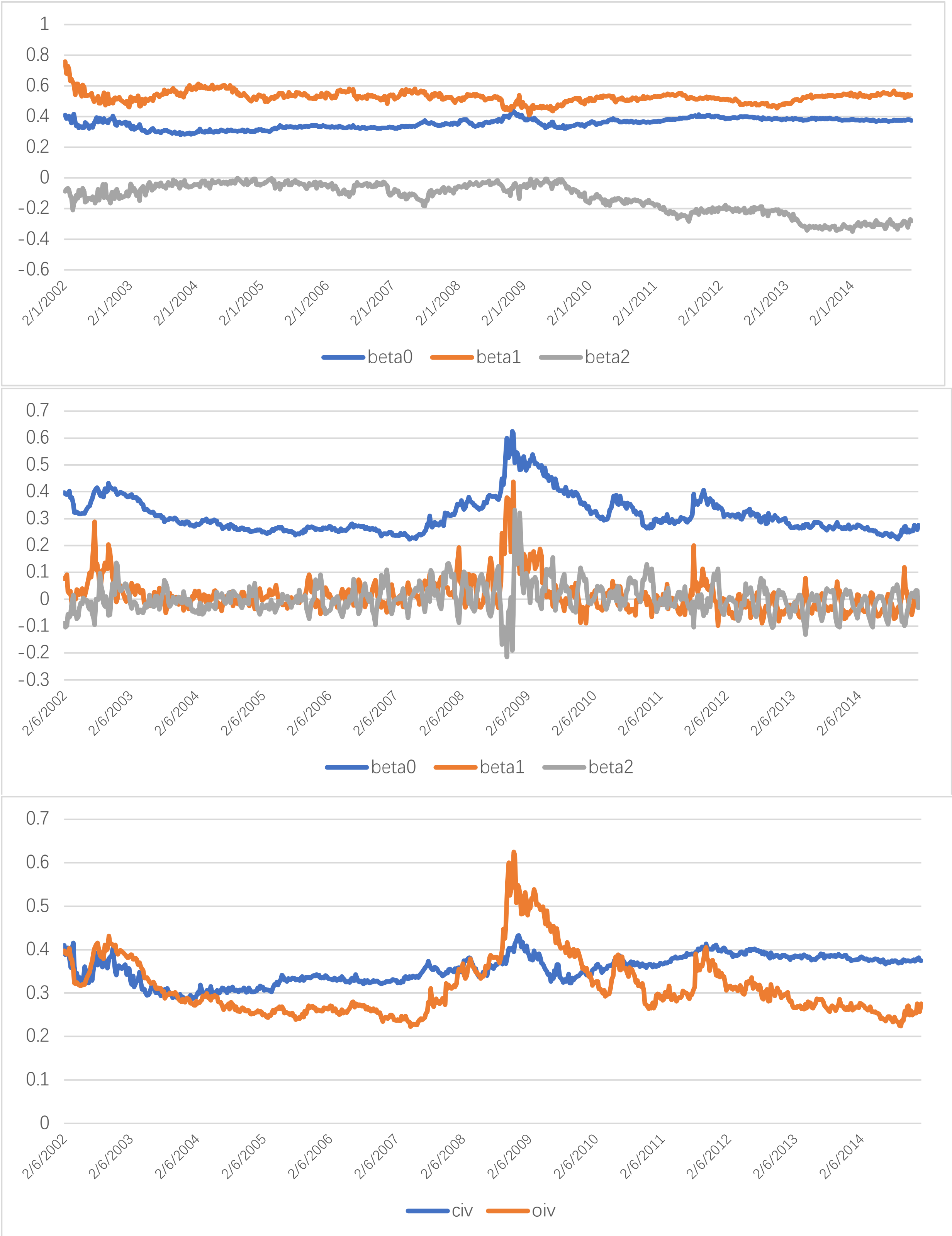

Table 7 presents the returns of the option portfolios constructed using the Z-score based on β_0. The results in Table 7 show a similar pattern as in Table 2. Specifically, the quintile straddle portfolio returns have an increasing pattern from bottom to top, ranging from -6.1% to 1.6% per month. The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

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

In summary, our conclusions are further supported by the robustness tests, whereby a Nelsen-Siegel model is fit, with variable maturities, and all tests are re-run. This further indicates that the abnormal straddle returns achieved based on the Z-score are unlikely to be driven by a certain maturity.

4.5 Transaction costs: bid-ask spreads

In the above tests, we take the mid-price as the trading price. However, in reality, an asset can only be bought at the ask price and can only be sold at the bid price. Literature shows evidence that the real bid-ask spread is smaller than the quoted bid-ask spread, but it is still significant (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 prices at the 25%, 50%, 75%, 100% range of the quoted bid-ask spread in trading straddles.

We also group option portfolios by liquidity to address concerns about the impact of liquidity risk. In addition, we compute two different measures to access liquidity. The first measure is the average bid-ask spread of all options traded in the previous month for the firm and the second measure is the average daily trading volume of options traded in the previous month for the firm. We first sort options into quintile portfolios based on the Z-scores. Then, in each quintile straddle portfolio, we sort options into two portfolios with low and high liquidity. The returns of the 5-1 and P/N portfolios are subsequently computed for each portfolio.

Table 8 reports the long-short portfolios under different efficient bid-ask spreads. Accounting for transaction costs leads to a deterioration in the performance of the long-short strategy. Without transaction costs, the 5-1 portfolio earns 6.96% monthly raw return. However, this return decreases dramatically to -4.5% per month under the condition of a 100% efficient bid-ask spread. The P/N portfolios exhibit the same effect, whereby raw returns fall from 4.7% per month to -6.5% per month. However, De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) report that the effective-to-quoted spread ratio is lower than 50%. Thus, 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%, respectively, for the 5-1 portfolio and 2% and 2.3%, respectively, for the P/N portfolio.

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%. However, this return is still significant at the 5% significance level under the 50% quoted spread condition, with a monthly return of 5.4%. By contrast, 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 this return is significant at the 1% level based on the 25% quoted spread, with a monthly return of 5.1%. The return of the high liquidity portfolio decreases dramatically from 2.5% to -10.8%. If the other measure of liquidity based on the average trading volume of options is applied, returns exhibit 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 as the effective-to-quoted spread ratios become larger. Nevertheless, they are still significant when the ratio is at 25% or less. In addition, returns are more significant for less liquid options.

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

4.6 Subsample analysis around the Global Financial Crisis (GFC)

In this section, we conduct a robustness test using sample periods around the GFC. 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% for the bottom and top portfolios. 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 returns at the 10% significance 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. Hence, despite the increasing standard deviation of sorted portfolio returns, our findings remain robust.

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

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 of equally-weighted portfolios and construct a zero-cost trading strategy that is long (short) in the portfolio with the largest (smallest) Z-score. The strategy generates a significant average raw monthly return of 6.96%, with a t-statistic of 2.89.

The achievement of abnormal returns when portfolios are sorted by Z-score cannot be fully explained by traditional stock risk factors, nor by stock characteristics. The alphas of the long-short straddle portfolios remain significant, irrespective of whether the Fama-French three-factor model, the Carhart four-factor model, or the excess return of the zero-beta ATM S&P 500 index systematic straddle factor by Coval and Shumway (2001) is applied as a benchmark. Double sorts confirm the predictive power of the Z-score and the returns hold for alternative definitions of the Z-score. Transaction costs do reduce the profits. Nevertheless, the profits 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 the CDS market when making investment decisions.

References

Bali, T., and S. Murray. “Does Risk-Neutral Skewness Predict the Cross Section of Equity Option Portfolio Returns?” Journal of Financial and Quantitative Analysis, 48 (2013), 1145–1171.

Balvers, R., Wu, Y. R., & Gilliland, E. (2000). Mean reversion across national stock markets and parametric contrarian investment strategies. *Journal of Finance*, 2, 745–772.

Brennan, M. J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns1. *Journal of Financial Economics*, *49*(3), 345-373.

Cao, J., and B. Han. “Cross Section of Stock Option Returns and Stock Volatility Risk Premium.” Journal of Financial Economics, 108 (2013), 231–249.

Cao, C., Yu, F., & Zhong, Z. D. (2010). The information content of option-implied volatility for credit default swap valuation. Journal of Financial Markets, 12, 321–343.

Carr, P., & Wu, L. R. (2007). Theory and evidence on the dynamic interactions between sovereign credit default swaps and currency options. Journal of Banking & Finance, 31, 2383–2403.

Carr, P.,&Wu, L. R. (2010a). Stock options and credit default swaps: A joint framework for valuation and estimation. Journal of Financial Econometrics, 8, 409–449.

Carr, P., & Wu, L. R. (2010b). A simple robust link between American puts and credit protection. Review of Financial Studies, 24, 474–505.

Coval, J. D., & Shumway, T. (2001). Expected option returns. *The journal of Finance*, *56*(3), 983-1009.

De Fontnouvelle, P., Fishe, R. P., & Harris, J. H. (2003). The Behavior of Bid‐Ask Spreads and Volume in Options Markets during the Competition for Listings in 1999. *The Journal of Finance*, *58*(6), 2437-2463.

Gang, J.H., Zhao, Y., Ma X.C. (2019). Put-call ratio predictability of the 50ETF option. *Journal of Economic and Political Studies*, 7(3), 352-376.

Goyal, A., Saretto, A. (2009). Cross-section of option returns and volatility. *Journal of Financial Economics*, 94(2), 310-326.

Guo, B., Han, Q., & Zhao, B. (2014). The Nelson–Siegel model of the term structure of option implied volatility and volatility components. *Journal of Futures Markets*, *34*(8), 788-806.

Guo, B. (2016). CDS Inferred Stock Volatility. *Journal of Futures Markets*, *36*(8), 745-757.

Han, B., Subrahmanyam, A., Zhou, Y. (2017). The term structure of credit spreads, firm fundamentals, and expected stock returns. Journal of Financial Economics, 124(1), 147-171.

Hanna, J., Ready, M., 2005. Profitable predictability in the cross section of stock returns. *Journal of Financial Economics* 78, 463–505

Heston, S. L. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *The review of financial studies*, *6*(2), 327-343.

Kelly, B. T., Manzo, G., Palhares, D. (2017). Credit-Implied Volatility. *Chicago Booth Research Paper* No. 17-12.

Mayhew, S., 2002. Competition, market structure, and bid–ask spreads in stock option markets. *Journal of Finance* 57, 931–958.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, *29*(2), 449-470.

Nelson, C. R., & Siegel, A. F. (1987). Pparsimonious modeling of yield curves. *Journal of Business*, 60(4), 473-489.

Park, Y.‐H. (2011). The roles of short‐run and long‐run volatility factors in options market: A term structure perspective. Available at SSRN: http://ssrn.com/abstract¼1783937 or doi: 10.2139/ssrn.1783937.

Stein, J. C. (1989). Overreactions in the options markets. *Journal of Finance*, 44, 1011–1023.

Vasquez, A. (2017). Equity Volatility Term Structures and the Cross Section of Option Returns. *Journal of Financial and Quantitative Analysis*, 1-28.