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Do changes in the implied volatility of stock options predict future changes in CDS spreads?

Journal of Derivatives and Quantitative Studies: 선물연구

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Received 2 December 2024
Revised 27 January 2025
20 February 2025
Accepted 20 February 2025

Abstract
This study examines whether changes in the implied volatility of stock options have cross-sectional predictability for future changes in credit default swap (CDS) spreads in the Korean market. The major findings are as follows. First, in the CDS portfolio analysis, when buying a portfolio with the highest increases in implied volatility and selling a portfolio with the highest decreases and rebalancing monthly, the average change in future CDS spreads is positive and statistically significant. Second, the cross-sectional predictive regression analysis shows that the coefficients for changes in implied volatility are significant in most models. The magnitude of the coefficients remains generally stable regardless of the control variables. These findings provide further evidence supporting the perspective of Cao *et al.* (2023) that increases in implied volatility reflect information about increased default risk due to higher firm value volatility.

Keywords CDS, Stock option, Implied volatility, Default risk
Paper type Research paper

1. Introduction

Many studies have consistently presented evidence supporting the claim by Easley *et al.* (1998) that informed traders prefer to trade in the options market ahead of other markets. We can easily find papers that test the cross-sectional predictive power of various stock option-related variables for future stock returns or conduct time-series analyses of information transmission from the options market to the stock market. However, as noted by Cao *et al.* (2023), there is relatively little research on whether the stock options market reflects information related to future bond returns and thereby plays a price discovery role for the bond market. To address this, they investigate whether changes in the implied volatility of individual stock options have cross-sectional predictability for future bond returns.

A representative study that examines the predictive power of changes in implied volatility is An *et al.* (2014), which insists that changes in implied volatility convey information about fundamental news. The study assumes that increases in call option implied volatility are driven by good fundamental news about the firm, while increases in put option implied volatility are driven by bad fundamental news. They find that changes in call option implied volatility predict higher future stock returns, while changes in put option implied volatility predict lower future stock returns. These findings support their fundamental news hypothesis.

JEL Classification — G12, G14

This research was funded by the Hallym University Research Fund (HRF-202403-001).

Journal of Derivatives and Quantitative Studies: 선물연구
Emerald Publishing Limited
e-ISSN: 2713-6647
p-ISSN: 1229-988X
DOI 10.1108/JDQS-12-2024-0048

On the other hand, Cao *et al*. (2023) provide a different interpretation of the changes in the implied volatility of individual stock options compared to previous studies. The authors argue that changes in implied volatility reflect information about uncertainty shocks to the firm or its default risk. They assume that increases in the implied volatility of both call and put options are driven by an increase in the volatility of firm value. Using the average implied volatility change of call and put options for each firm as their implied volatility change variable, they demonstrate that firms with larger changes in implied volatility tend to have lower future bond returns compared to those with smaller changes. This finding confirms the predictive power of implied volatility. Furthermore, they find that when using the difference between the call option implied volatility change and the put option implied volatility change, the key variable in An *et al*. (2014), as the implied volatility change variable, it fails to predict future bond returns. This provides evidence that contradicts the fundamental news claim of An *et al*. (2014) and suggests that stock option implied volatility conveys information to bond returns that differs from the information it conveys to stock returns [1].

This study aims to extend the research mentioned above by examining whether the implied volatility of individual stock options in the Korean market reflects information about default risk and whether it has predictive power. Instead of using corporate bond yields, this study uses credit default swap (CDS) spreads, which are based on corporate bonds, to investigate whether information about default risk is conveyed.

The backgrounds for utilizing CDS as the subject of analysis are as follows. First, an individual company's CDS is a contract that promises compensation for losses if the bonds issued by that company default, in exchange for receiving premiums. Unlike corporate bond yields, which can be influenced by other risk factors such as bond market returns, liquidity risk, and downside risk, CDS premiums (i.e. CDS spreads) are more directly related to the company's default risk. Second, Lee *et al*. (2018) demonstrate that when firm-specific credit risk information is dominant, the CDS market leads both the stock and bond markets for US companies. This implies that when a company's credit risk is the most critical issue, the CDS market plays a key role in price discovery. Therefore, this study aims to observe whether the stock option market leads the CDS market, which has been shown to respond more quickly to credit risk information than the bond market, with a focus on Korean companies.

This study is similar to the research by Cao *et al*. (2023), but their focus is primarily on examining the cross-sectional relationship between changes in implied volatility and bond returns in the US market. Although the paper also replaces bond yields with changes in CDS spreads to explore the relationship with changes in implied volatility, it only reports this in a single table as a robustness check. The main differences between this study and the paper by Cao *et al*. (2023) are as follows. First, this study focuses on examining the cross-sectional relationship between changes in CDS spreads and changes in implied volatility in the Korean market. Second, instead of solely conducting cross-sectional regression analysis, this study also incorporates portfolio analysis and subsample analysis with and without the inclusion of the financial crisis period, providing a more in-depth investigation into the relationship between the two asset markets. Third, in the baseline analysis, implied volatility is calculated using near-the-money options. Additionally, implied volatility is recalculated by utilizing options that are closer to at-the-money to perform robustness checks. The final and most significant difference lies in the calculation of the implied volatility change variable. In this study, the analysis utilizes the average implied volatility change of call, put, and straddle options, as well as the average implied volatility change of put and call options.

This study examines whether changes in the implied volatility of stock options have cross-sectional predictive power for future changes in CDS spreads, focusing on 19 Korean companies for which both 5-year CDS spread data and over-the-counter (OTC) stock option data are available from April 2005 to October 2012. When calculating implied volatility, near-the-money options with strike prices corresponding to 80%–120% of the stock price and maturities of 180 days or more are used. The average implied volatility of put and call options is defined as the Implied Volatility 1 variable, while the average implied volatility of call, put, and straddle options is defined as the Implied Volatility 2 variable, enabling a comparative analysis.

The main findings are as follows: First, in the portfolio analysis, when constructing a strategy of buying the portfolio with the largest increase in implied volatility and selling the portfolio with the largest decrease in implied volatility, and rebalancing monthly, the average future change in CDS spreads is positive and statistically significant. Second, the cross-sectional predictive regression analysis using the Fama-Macbeth (1973) method shows that the coefficients of the implied volatility change variables are positive and significant in most models. The magnitude of the coefficients remains generally stable regardless of the control variables, confirming the cross-sectional predictive power of implied volatility changes for future CDS spread changes. Notably, while the model by Cao *et al*. (2023) for the US market demonstrates an explanatory power of approximately 20%, the analysis model in this study for the Korean market exhibits a higher explanatory power of around 30%. Third, in both portfolio analysis and regression analysis, the predictive power of the Implied Volatility 2 variable is higher than that of the Implied Volatility 1 variable during periods including the financial crisis. This suggests that the implied volatility of straddle options contains additional information about default risk during financial crisis. In contrast, during normal periods excluding the financial crisis, models incorporating changes in Implied Volatility 1 demonstrates higher explanatory power than those including Implied Volatility 2. Finally, to mitigate the impact of the volatility smile, robustness checks are performed by recalculating the implied volatility variables using options closer to at-the-money. The results continue to support the predictive power of changes in implied volatility.

This study makes the following contributions to existing research: First, similar to the paper by Cao *et al*. (2023), which demonstrates that changes in implied volatility of stock options have cross-sectional predictive power for CDS spread changes in the US market, this study finds that the same predictive power exists in the Korean market. Ultimately, we provide additional evidence supporting the perspective of Cao *et al*. (2023) that an increase in implied volatility reflects information about the increased default risk due to greater volatility in firm value. At the same time, our findings demonstrate that the fundamental news claim proposed by An *et al*. (2014) may be limited to its predictive power for stock returns.

Second, this study presents results consistent with the paper by Cao *et al*. (2023), which insists that “informed traders prefer to trade in the options market first when new information about firm risk arises, while the bond or CDS markets reflect that information more slowly.” This provides additional evidence to numerous existing studies showing that the options market has a superior price discovery function compared to other markets. In particular, Kim and Park (2013) demonstrate, based on data from 2003 to July 2009, that CDS term structure slopes for the individual firms have cross-sectional predictive power for future stock returns in the Korean market. As this study shows that the individual stock options market has an edge over the CDS market in terms of information reflection over a similar period, it provides an indication of the superior information efficiency of the individual stock options market among various asset markets in Korea.

Third, unlike previous studies, this research generates an average implied volatility change variable that includes the implied volatility change of straddle options. It finds that the predictive power of implied volatility changes improves for periods including the financial crisis. This suggests that the degree or speed of reflecting default risk information may vary depending on the type of option.

The structure of this study is as follows: Section 2 reviews previous research, and Section 3 describes the data used in the study. Section 4 presents the results of the empirical analysis. Finally, Section 5 provides the conclusion and discusses the limitations of the study.

2. Literature review

Among the papers that analyze the relationship between stock options and CDS in the US market, excluding those focusing on index options, the ones that specifically examine the relationship between stock options and CDS for individual companies include Cao *et al.* (2010), Carr and Wu (2011), Kim *et al.* (2013), Wang *et al.* (2013), Cao *et al.* (2021) and Shi *et al.* (2022).

Cao *et al.* (2010) aim to identify whether the implied volatility of put options is a significant determinant of CDS spreads. They find that the implied volatility of put options is superior to historical volatility in explaining the time-series variation of CDS spreads for individual companies. Furthermore, when regressing expected future volatility proxy and volatility risk premium as independent variables, they show that both variables play a significant role in determining CDS spreads. Therefore, it can be interpreted that implied volatility explains CDS spreads because it not only predicts future volatility but also reflects the time-varying volatility risk premium.

Carr and Wu (2011) assume a unit recovery claim (URC), which pays 1 dollar in the event of default and 0 otherwise. The value of a URC for a single company can be calculated using the individual company's deep-out-of-money put option price, as well as the CDS spread and recovery rate. Carr and Wu (2011) prove this mathematically and report that there is a high correlation between the URCs calculated from the two assets.

Kim *et al.* (2013) propose a more refined method for calculating the URC suggested by Carr and Wu (2011), by incorporating the strike price of deep-out-of-the-money put options and the recovery rate in a more precise manner. They calculate the adjusted URCs from the two assets and examine the variables that affect the difference between the two measures. They find that during the financial crisis, the impact of macroeconomic variables on the difference increases. Additionally, they show that during the financial crisis, the changes in the adjusted URC calculated from options lead the changes in the adjusted URC calculated from CDS spreads, compared to normal periods.

Wang *et al.* (2013) derive the variance risk premium from option prices for individual company and examine whether it explains the cross-section of CDS spreads. As a result, they find that the variance risk premium has significant explanatory power, and its impact does not disappear even when controlling for market or firm-level credit risk factors. In addition, they demonstrate that the explanatory power of the variance risk premium for individual company is stronger than that of the market-level variance risk premium, which reflects the systematic variance risk embedded in CDS spreads, or the volatility index (VIX), which can reflect economic uncertainty.

Cao *et al.* (2021) seek to investigate whether the introduction of one derivative affects other derivative markets. To do so, they examine whether the issuance of a company's CDS leads to changes in the company's stock option prices. They find that when both the CDS and options of the same company exist simultaneously, the option prices are higher compared to when the CDS is not present, as observed through delta-hedged option returns. These results remain unchanged even after controlling for various variables that predict option returns. Moreover, they find that after the issuance of a new CDS for a company, the demand for options on that company by dealers or brokers increases. This supports the demand-based option pricing theory, which states that market makers price options higher when facing increased demand.

Shi *et al.* (2022) extend the theory of Carr and Wu (2011) by using the URC to bridge the CDS and deep-out-of-the-money put options of the same company and calculate the CDS implied volatility (CIV) using a binomial tree model. They also confirm a high correlation between the CDS implied volatility (CIV) and the option implied volatility (OIV). Furthermore, they show that when using both measures to implement the long-short CDS trading strategy, a high annual return and a positive Sharpe ratio can be achieved, without considering transaction costs.

In the context of the Korean market, the papers that analyze the relationship between individual stock options and CDS or bonds are those by Hong and Baek (2016) and Park and Kim (2012).

Hong and Baek (2016) analyze whether the implied volatility of OTC individual stock options is a significant determinant of corporate bond credit spreads by extending the variables used in traditional structural models. The results of a pooled regression analysis, which includes market variables and macroeconomic variables, confirm that the implied volatility of individual stock options is an important factor reflecting a firm's credit risk information. Moreover, unlike the results from the US market, the Korean market shows higher explanatory power for short-term corporate bonds compared to long-term bonds. Additionally, regression analysis by option type reveals that the put option variable exhibits the highest statistical significance for both short-term and long-term credit spreads.

Park and Kim (2012) aim to verify whether the implied volatility of out-of-the-money put options, estimated from OTC individual stock options, explains the variation in CDS spreads. The results show that implied volatility exhibits superior explanatory power compared to historical volatility. Additionally, they find that the predicted future volatility and volatility risk premium estimated from implied volatility are important determinants of CDS spreads in out-of-sample tests. In particular, these variables show a stronger impact during financial crisis.

While Park and Kim (2012) focus on the time-series explanatory power of implied volatility of individual stock options on CDS spreads, this study differs by focusing on the cross-sectional predictive power of implied volatility of OTC individual stock options on future CDS spreads. Also, while Park and Kim (2012) only utilized the implied volatility of out-of-the-money put options, this study examines the relationship with CDS spreads using the implied volatilities of near-the-money call, put, and straddle options.

3. Data and variable description

3.1 Change in CDS spread

The CDS spread data is collected from Markit for CDS based on senior unsecured dollar-denominated bonds of Korean companies from April 2005 to October 2012. The 5-year maturity spread, which has been reported to have the highest trading volume in CDS literature, is selected for analysis. Among these, only companies for which both the 5-year CDS spread data and OTC stock option data are available simultaneously are selected as the sample. Ultimately, 19 companies are chosen as the sample firms.

To calculate monthly spread changes, the daily CDS spreads for each firm are averaged monthly and converted into a monthly time series. Future CDS spread changes are then computed using the following formula such as Equation (1), by subtracting the average 5-year CDS spread of firm i in month t from the average 5-year CDS spread of firm i in month $t+1$.

$$\Delta CDS_{i,t+1} = CDS_{i,t+1} - CDS_{i,t} \tag{1}$$

Where $CDS_{i,t}$: the average 5-year CDS spread of firm i in month t.

3.2 Change in implied volatility of stock option

OTC stock option data are collected as follows, based on the method of Hong and Baek (2016). First, daily option premium quotes are collected from Cscreen (information provider), Nittan (brokerage company), and Korean banks dealing with OTC options. Subsequently, the implied volatility is extracted using the formula of Black and Scholes (1973). If there is a traded price, the implied volatility calculated from the traded price is used. If not, the mid-point of the implied volatilities calculated from the bid and ask prices is used.

While Hong and Baek (2016) utilize OTC stock options with maturities ranging from 30 to 367 days, this study restricts the analysis to long-term options with maturities of 180 days or more, given that the CDS spreads analyzed have a maturity of 5 years. In addition, when calculating implied volatility, only near-the-money options with strike prices corresponding to 80%–120% of the stock price are used.

When calculating the call option implied volatility (CVOL), put option implied volatility (PVOL), and straddle option implied volatility (SVOL), the equally weighted average implied volatility by strike price for each company is calculated daily and then averaged monthly to convert it into a monthly time series. Then, Implied Volatility 1 (IMVOL1) is calculated as the average of the implied volatilities of call options and put options ((CVOL + PVOL)/2). Implied Volatility 2 (IMVOL2) is calculated as the average of the implied volatilities of call options, put options, and straddle options ((CVOL + PVOL + SVOL)/3) [2].

The change in implied volatility is calculated as the difference between the average implied volatility of month *t* and the average implied volatility of month *t-1* for company *i*, as shown in Equation (2). In other words, the change in IMVOL1 (or IMVOL2) is calculated by subtracting the previous month's average IMVOL1 (or IMVOL2) from the current month's average IMVOL1 (or IMVOL2) for each company.

$$\Delta IMVOL_{i,t} = IMVOL_{i,t} - IMVOL_{i,t-1} \tag{2}$$

3.3 Descriptive statistics

Table 1 shows the mean, standard deviation (Std), minimum (Min), and maximum (Max) values of future CDS spread changes for each company. Additionally, it shows the average monthly changes in the implied volatility of stock options for each company. The last column displays the number of observations (Num. of Obs.) observed monthly for each company. The companies with the largest average future CDS spread changes are SK Hynix and Hana Financial, with approximately 27bps and 9bps, respectively. On the negative side, the companies with the largest changes are Samsung Heavy Industries and Hyundai Heavy Industries, with approximately −27bps and −11bps, respectively.

The company with the largest average change in IMVOL1 is SK, but since the number of observations is only 8 months, it can be excluded from consideration. Excluding SK, the companies with the largest average changes are SK Hynix and Hana Financial, with 0.51% and 0.22%, respectively. The company with the largest negative average change in IMVOL1 is Korea Gas Corporation, but it can be excluded due to only having one month of observations. Excluding Korea Gas Corporation, the companies with the largest negative average changes are KB Financial and SK Energy, with −2.43% and −1.45%, respectively.

The companies with the largest average change in IMVOL2 are SK Hynix and Hana Financial, with values of 0.39% and 0.45%, respectively. The company with the largest negative average change in IMVOL2 is Korea Gas Corporation, but it can be excluded due to only having one month of observations. Excluding Korea Gas Corporation, the companies with the largest negative average changes are KB Financial and SK Energy, with −2.36% and −1.64%, respectively.

Consequently, companies with the largest increases in future CDS spreads also tend to have large increases in IMVOL1 and IMVOL2, supporting the cross-sectional predictive power of changes in implied volatility for future changes in CDS spreads. On the other hand, the companies with the largest decreases in future CDS spreads generally have large decreases in IMVOL1 and IMVOL2, but they are not the largest. Therefore, it is difficult to strongly support the predictive power. As indicated in the last column, the number of observations varies by company, which may influence these results. Therefore, we intend to examine this in more detail through regression analysis.

Table 2 shows the cross-sectional mean, standard deviation (Std), 5th percentile, and 95th percentile of the levels and changes of implied volatility variables, along with the future CDS spread changes for each company. It also provides cross-sectional summary statistics of firm-level credit-related variables that are expected to explain changes in CDS spreads. Panel A

Table 1. Changes in the implied volatility and changes in CDS spreads

Short name of company	Δ Future CDS spread (bps) Mean	Std	Min	Max	Δ IMVOL1 (%) Mean	Δ IMVOL2 (%) Mean	Num. of obs. (month)
Samsung Heavy Inds	−26.70	6.86	−36.84	−17.78	−0.38	−0.38	4
Hyundai Heavy Inds	−11.23	24.35	−59.10	30.97	−0.70	−0.75	25
SK	−5.90	5.82	−17.29	−0.06	2.39	0.32	8
KT	−3.78	25.76	−115.29	44.19	−0.25	−0.24	32
KB Financial	−2.58	21.83	−40.39	74.17	−2.43	−2.36	29
LG Elec	−0.57	43.34	−112.17	250.33	−0.05	−0.15	71
SK Energy	−0.34	65.96	−175.39	262.95	−1.45	−1.64	32
Samsung Elec	−0.21	33.29	−106.35	216.91	−0.19	−0.07	77
Hyundai Motor	0.11	57.19	−224.96	310.69	−0.18	0.06	73
POSCO	0.24	38.15	−109.00	232.76	−0.18	−0.17	69
SK Telecom	0.64	51.18	−107.60	239.77	−0.23	−0.41	35
Korea Elec Pwr	0.68	41.00	−119.78	237.76	−0.14	−0.04	66
LG Display	1.06	80.55	−303.73	378.09	−0.20	−0.54	53
Shinhan Financial	1.20	55.29	−156.35	313.94	−0.86	−0.97	69
Korea Gas	3.31	0.00	3.31	3.31	−2.26	−2.26	1
Woori Financial	6.23	69.45	−171.95	331.73	0.17	−0.41	51
Kia Motor	7.84	32.01	−79.28	117.34	0.06	−0.04	29
Hana Financial	8.84	71.43	−120.31	312.93	0.22	0.45	26
SK Hynix	27.26	201.95	−489.25	923.64	0.51	0.39	49

Source(s): The authors

presents the statistics for the entire sample period, while Panel B shows the statistics for the sample excluding the financial crisis period from January 2008 to August 2009.

The three credit-related variables are calculated by averaging the daily time series into a monthly time series. Specifically, the CDS percentage changes are calculated by dividing the current month's spread changes by the previous month's CDS spread [3]. The firm stock return is calculated by dividing the current month's stock price changes by the previous month's stock price. CDS liquidity is measured by the monthly average number of brokers providing 5-year CDS spread quotes.

In Panel A, the cross-sectional average of CDS spread changes is approximately 5bps, with a standard deviation of about 15bps. The average implied volatilities of call options, put options, and straddle options are 31.4%, 34.3%, and 32.9%, respectively. The average IMVOL1 and the average IMVOL2 are 33.6% and 32.9%, respectively. The average changes in IMVOL1 and IMVOL2 are −0.36% and −0.47%, respectively. The average value of CDS percentage changes is 2.94%, and the average value of stock returns is measured at 0.68%. The cross-sectional average number of brokers providing CDS spread quotes per month is approximately 6.88, or about 7 brokers, with a standard deviation of about 3 brokers.

Table 2. Summary statistics

Variables	Mean	Std	5th percentile	95th percentile
Panel A: full sample period				
CDS spread variable				
Δfuture CDS spreads (bps)	5.173	14.699	−15.532	29.415
Option-implied volatility variables				
ΔCVOL (%)	0.320	1.340	−1.223	2.206
ΔPVOL (%)	−0.399	1.582	−2.641	1.121
ΔSVOL (%)	−0.160	1.381	−3.011	1.311
ΔIMVOL1 (%)	−0.361	1.548	−2.589	1.207
ΔIMVOL2 (%)	−0.469	0.967	−2.500	0.390
CVOL (%)	31.398	5.911	19.392	37.900
PVOL (%)	34.303	4.082	26.798	38.319
SVOL (%)	32.875	4.646	26.600	39.135
IMVOL1 (%)	33.641	4.097	25.413	37.828
IMVOL2 (%)	32.925	4.301	25.434	38.215
Firm-level credit-related variables				
CDS percentage changes (%)	2.941	6.868	−7.805	11.058
Firm stock returns (%)	0.677	2.623	−1.573	2.613
CDS liquidity	6.884	3.035	2.100	10.724
Panel B: sample period excluding the global financial crisis				
CDS spread variable				
Δfuture CDS spreads (bps)	−1.522	7.109	−15.032	6.271
Option-implied volatility variables				
ΔCVOL (%)	1.061	1.030	−0.681	2.866
ΔPVOL (%)	0.148	1.364	−2.027	1.499
ΔSVOL (%)	−0.190	0.800	−1.899	0.588
ΔIMVOL1 (%)	0.230	1.317	−2.027	1.202
ΔIMVOL2 (%)	−0.037	0.883	−2.027	1.018
CVOL (%)	27.617	5.657	18.316	35.855
PVOL (%)	30.529	3.853	24.082	34.901
SVOL (%)	29.527	3.778	24.782	35.688
IMVOL1 (%)	29.876	4.255	22.315	34.809
IMVOL2 (%)	29.141	4.024	22.277	33.816
Firm-level credit-related variables				
CDS percentage changes (%)	0.156	6.494	−9.607	8.734
Firm stock returns (%)	1.396	2.301	−0.134	2.413
CDS liquidity	6.661	3.043	2.115	10.807

Source(s): The authors

In Panel B, the cross-sectional average of CDS spread changes is approximately −1.5bps, with a standard deviation of about 7bps. The average implied volatilities of call options, put options, and straddle options are 27.6%, 30.5%, and 29.5%, respectively. The average IMVOL1 and the average IMVOL2 are 29.9% and 29.1%, respectively. The average changes in IMVOL1 and IMVOL2 are 0.23% and −0.03%, respectively. This is consistent with Cao *et al*. (2023), which indicates that the average changes in implied volatilities of options are close to zero. The average value of CDS percentage changes is 0.16%, and the average value of stock returns is measured at 1.4%. The cross-sectional average number of brokers providing CDS spread quotes per month is approximately 6.66 with a standard deviation of about 3 brokers. We confirm that the average values of most variables, except for firm stock returns, are lower in the sample excluding the global financial crisis compared to those in the full sample.

4. Empirical analysis

4.1 Analysis of CDS portfolios sorted on change in implied volatility

Table 3 classifies the portfolio into quartiles based on changes in IMVOL1 and shows the average monthly change in future CDS spreads for each portfolio. Low-1 is the portfolio of companies with the smallest changes in IMVOL1, while High-4 is the portfolio of companies with the largest changes in IMVOL1. The portfolio is reconstituted every month, but only if the number of cross-sectional data points for that month is 6 or more. H-L represents the average change in future CDS spreads when buying the High-4 quartile portfolio and selling the Low-1 quartile portfolio each month. The numbers in parentheses indicate the *t*-statistics. (*p*-value: ***<0.01, **<0.05 and *<0.10) The rows below report the average values of firm-level credit-related variables for each quartile. Panel A covers the entire sample period, while Panel B shows the results for the sample excluding the financial crisis period.

Looking at the results of Panel A, the average change in future CDS spreads for Low-1 is −0.079bps, while the average change for High-4 is 4.313bps. This means that the portfolio with the largest change in IMVOL1 exhibits a positive average change, whereas the portfolio with the smallest change in IMVOL1 exhibits a negative average change. The result aligns with the research hypothesis that greater changes in implied volatility are associated with larger changes in future CDS spreads. However, the change in CDS spreads does not show a monotonic increase as the change in IMVOL1 increase. Instead, the change in CDS spreads rises to the third quartile portfolio and then decreases in the fourth quartile. All the average values are statistically insignificant. This may be attributed to the fact that the CDS and options markets in Korea are not well-developed, resulting in a small sample size of collected firms and a varying number of cross-sectional data points each month, leading to potential noise in the calculated values.

Nevertheless, some meaningful results are observed. For the H-L portfolio, which involves buying the portfolio with the highest change in implied volatility and selling the portfolio with the lowest change in implied volatility, the average change in CDS spread is 4.392 bps, which is significant at the 10% level.

In the rows below, the percentage change in CDS shows a decreasing trend from the Low-1 portfolio to the High-4 portfolio, while no clear patterns are identified for the other two variables. Thus, since the relationship between future changes in CDS spreads and changes in IMVOL1 may potentially be explained by the percentage change in CDS, this study aims to examine the impact of this variable in detail through a cross-sectional regression analysis.

Examining the results of Panel B reveals that the average future CDS spread change for Low-1 is −2.581 bps, while for High-4, it is 1.122 bps. Similar to Panel A, the portfolio with

Table 3. CDS portfolios sorted on ΔIMVOL1

	Low-1	2	3	High-4	H-L
Panel A: full sample period					
Average change	−0.079	6.420	7.291	4.313	4.392*
	(−0.01)	(0.99)	(0.77)	(0.57)	(1.89)
CDS percentage change (%)	5.066	4.810	4.488	0.471	
Firm stock return (%)	0.791	0.138	0.329	1.394	
CDS liquidity	7.214	7.634	7.299	7.172	
Panel B: sample period excluding the global financial crisis					
Average Change	−2.581	2.904	0.623	1.122	3.703**
	(−1.07)	(0.98)	(0.26)	(0.37)	(2.12)
CDS percentage change (%)	4.691	4.335	3.662	−0.837	
Firm stock return (%)	0.541	−0.166	0.623	1.921	
CDS liquidity	7.076	7.218	6.739	7.032	

Source(s): The authors

the largest change in IMVOL1 shows, on average, a positive change, while the portfolio with the smallest change in IMVOL1 exhibits a negative change. However, these values are not statistically significant. Additionally, future CDS spread changes do not show a monotonic increasing trend as portfolios move toward larger changes in IMVOL1, and the average values are not statistically significant.

However, in the case of the H-L portfolio, the average CDS spread change is 3.703 bps, which is significant at the 5% level. This indicates that a clearer spread difference between portfolios is observed when the financial crisis period is excluded compared to when it is included. Additionally, as in Panel A, the percentage change in CDS shows a decreasing trend from the Low-1 portfolio to the High-4 portfolio, while no clear patterns are identified for the other two variables.

We repeat the portfolio analysis using ΔCVOL−ΔPVOL, which is the main variable employed by An *et al*. (2014) and relevant to fundamental news, as the sorting variable. In unreported results, we find that the average CDS spread change values for all portfolios are not statistically significant. For the H-L portfolio, the average value is −6.53 bps, with a *t*-statistic of −1.55 for the full sample period, and −1.35 bps, with a *t*-statistic of −0.58 for the sample period excluding the global financial crisis. These results contradict the claim made by An *et al*. (2014) that an increase in call option implied volatility is driven by good fundamental news, while an increase in put option implied volatility is driven by bad fundamental news.

Table 4 classifies quartile portfolios based on changes in IMVOL2 and presents the monthly average future CDS spread changes for each portfolio. Low-1 represents the portfolio of firms with the smallest changes in IMVOL2, while High-4 represents the portfolio of firms with the largest changes in IMVOL2. The numbers in parentheses represent the *t*-statistics. (*p*-value: ***<0.01, **<0.05 and *<0.10).

Looking at the results of Panel A, the average change in future CDS spreads for Low-1 is −0.18bps, while the average change for High-4 is 3.926bps. Like the results for IMVOL1, this aligns with the research hypothesis that greater changes in implied volatility are associated with larger changes in future CDS spreads, but none of the values are statistically significant. Additionally, like the results for IMVOL1, the change in CDS spreads for portfolios with greater changes in IMVOL2 shows an increase up to the third quartile portfolio and then a decrease in the fourth quartile. All average values are not statistically significant.

However, in the case of the H-L portfolio, which involves buying the portfolio with the highest change in IMVOL2 and selling the portfolio with the lowest change, the average CDS spread change is 4.107 bps, which is significant at the 5% level. This result shows a more positive outcome compared to the changes in IMVOL1 from Table 3. This can be interpreted as

Table 4. CDS portfolios sorted on ΔIMVOL2

	Low-1	2	3	High-4	H-L
Panel A: full sample period					
Average Change	−0.180	3.514	6.242	3.926	4.107**
	(-0.03)	(0.62)	(0.84)	(0.6)	(1.99)
CDS percentage change (%)	4.570	5.125	3.565	1.839	
Firm stock return (%)	0.216	0.476	0.078	1.710	
CDS liquidity	7.489	7.970	7.984	7.521	
Panel B: sample period excluding the global financial crisis					
Average Change	−2.150	0.924	0.780	0.437	2.587*
	(−1.02)	(0.39)	(0.38)	(0.19)	(1.88)
CDS percentage change (%)	2.072	3.110	1.530	−1.681	
Firm stock return (%)	0.697	0.765	1.194	2.740	
CDS liquidity	7.295	7.717	7.920	7.340	

Source(s): The authors

indicating that adding straddle options to calculate IMVOL strengthens the relationship between future CDS spread changes and IMVOL over the entire sample period. However, we plan to observe whether this result holds when controlling for other variables in subsequent regression analyses.

In the rows below, unlike the results for IMVOL1, the percentage change in CDS shows an increasing trend from the Low-1 portfolio up to the second quartile, after which it decreases monotonically. No clear patterns are observed for the other two variables.

Looking at the results of Panel B, the average future CDS spread change for Low-1 is −2.15 bps, while for High-4, it is 0.437 bps. Like Panel A, the portfolio with the largest change in IMVOL2 shows, on average, a positive change, while the portfolio with the smallest change in IMVOL2 shows a negative change. However, none of these values are statistically significant. Additionally, like the results for IMVOL1 in Table 3, future CDS spread changes do not show a monotonic increasing trend as portfolios move toward larger changes in IMVOL2, and the average values are not statistically significant.

Meanwhile, in the case of the H-L portfolio, the average CDS spread change is 2.587 bps, which is statistically significant. However, it shows weak significance at the 10% level, displaying somewhat different behavior compared to when classified by IMVOL1 changes. In other words, when classified by changes in IMVOL2, a clearer spread difference between portfolios is observed when the financial crisis period is included, compared to when it is excluded.

In the rows below, the percentage change in CDS shows an increasing trend from the Low-1 portfolio up to the second quartile, after which it decreases. For the stock return variable, there is a monotonic increasing trend from the Low-1 portfolio to the High-4 portfolio. However, this trend contradicts the theoretical relationship between stock return increases and future CDS spread changes. Thus, we plan to set the stock return variable as a control variable in the regression analysis to reassess this relationship.

4.2 Predictive regression of change in implied volatility on change in CDS spread

We perform a Fama-Macbeth (1973) two-step cross-sectional regression analysis to examine the cross-sectional relationship between changes in implied volatility and future CDS spreads. Specifically, in the first step, we conduct predictive regressions across all firms on a monthly basis, and in the second step, we calculate the time-series averages of the cross-sectional regression coefficients and their statistics [4]. The model equation for the predictive regression analysis is defined using the following independent variables: change in implied volatility ($\triangle IMVOL$), implied volatility ($IMVOL$), stock returns (FSR), percentage change in CDS ($CDSR$), and the value of CDS liquidity divided by 100 ($CDSLiq$).

$$\text{Model1} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \varepsilon_i \tag{3}$$

$$\text{Model2} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \beta_2 IMVOL_{i,t} + \varepsilon_i \tag{4}$$

$$\text{Model3} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \beta_2 FSR_{i,t} + \varepsilon_i \tag{5}$$

$$\text{Model4} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \beta_2 CDSR_{i,t} + \varepsilon_i \tag{6}$$

$$\text{Model5} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \beta_2 IMVOL_{i,t} + \beta_3 CDSLiq_{i,t} + \varepsilon_i \tag{7}$$

$$\text{Model6} : \Delta CDS_{i,t+1} = \alpha + \beta_1 \Delta IMVOL_{i,t} + \beta_2 IMVOL_{i,t} + \beta_3 CDSR_{i,t} + \varepsilon_i \tag{8}$$

In Model 1, a univariate regression analysis is conducted to test the predictive power of changes in implied volatility for changes in CDS spreads. In Model 2, it is examined whether this predictive power holds even when controlling for the level of implied volatility [5]. In Model 3 and Model 4, it is observed whether the predictive power of the change in implied volatility is maintained when controlling for stock returns and CDS percentage change variables. The reason is that they show a pattern of increasing or decreasing from the portfolio with the smallest change in implied volatility to the portfolio with the largest change, as seen in Tables 3 and 4 In Model 5, the analysis controls for the CDS liquidity variable, which do not show a clear pattern as the portfolio quantile increases with changes in implied volatility in Tables 3 and 4, while also adding the implied volatility level variable. In Model 6, the analysis controls for the CDS percentage change variable, which generally shows a clear pattern as the portfolio quantile increases in Tables 3 and 4, while also adding the implied volatility level variable.

Table 5 shows the results of the predictive regression analysis of changes in IMVOL1 for future CDS spread changes. Panel A presents the results for the entire sample period, while Panel B shows the results for the sample period excluding the global financial crisis. The coefficients shown represent the time-series averages of the Fama-Macbeth cross-sectional regression coefficients, and the numbers in parentheses correspond to the Newey-West adjusted *t*-statistics. (*p*-value: ***<0.01, **<0.05, and *<0.10) The adj. R^2 represents the time-series average of the adjusted R-squared.

First, looking at the results in Panel A, in Model 1, when the change in IMVOL1 is used as the single explanatory variable in the regression analysis, β_1 is 0.013, which is positive and statistically significant at the 5% significance level. The adjusted R-squared is 2.5%. In Model

Table 5. Predictability of ΔIMVOL1 for change in CDS spread

Variable	Model1	Model2	Model3	Model4	Model5	Model6
Panel A: full sample period						
Intercept	0.000	−0.004	0.000	0.001	−0.005*	−0.005**
	(−0.46)	(−1.59)	(−0.53)	(1.06)	(−1.86)	(−2.02)
ΔIMVOL1	0.013**	0.008*	0.015**	0.012***	0.007*	0.007
	(2.54)	(1.70)	(2.55)	(2.70)	(1.94)	(1.29)
IMVOL1		0.014			0.015	0.017*
		(1.53)			(1.67)	(1.92)
FSR			−0.003			
			(−1.53)			
CDSR				0.005**		0.007***
				(2.34)		(3.15)
CDSLiq					0.007	
					(1.03)	
adj. R^2	0.025	0.07	−0.001	0.262	0.331	0.317
Panel B: sample period excluding the global financial crisis						
Intercept	0.000	−0.004	0.000	0.000	−0.004	−0.004
	(−0.04)	(−1.11)	(0.15)	(0.38)	(−1.13)	(−1.34)
ΔIMVOL1	0.009***	0.012***	0.011**	0.008***	0.009**	0.012***
	(2.79)	(3.57)	(2.45)	(2.96)	(2.31)	(4.11)
IMVOL1		0.012			0.012	0.014
		(1.07)			(1.08)	(1.26)
FSR			−0.002			
			(−0.90)			
CDSR				0.006**		0.007**
				(2.38)		(2.61)
CDSLiq					0.004	
					(0.57)	
adj. R^2	0.031	0.023	0.041	0.276	0.306	0.314

Source(s): The authors

2 and Model 3, when the level variable of IMVOL1 and the stock return variable are added, the coefficient of the change in IMVOL1, β_1, remains statistically significant at the 10% and 5% significance levels, respectively. However, the adjusted R-squared decreases compared to Model 1, indicating that these models are not appropriate. In Model 4, when the CDS percentage change variable is added, the coefficient of this variable is statistically significant, unlike the other control variables. Moreover, β_1 exhibits strong significance, and the adjusted R-squared for Model 4 is 26.2%, indicating a relatively higher explanatory power.

Meanwhile, in Model 5, when both the CDS liquidity variable and the IMVOL1 level variable are controlled, the significance of β_1 weakens. Furthermore, in Model 6, when both the CDS percentage change variable and the IMVOL1 level variable are controlled, the significance of β_1 disappears. However, since Model 5 demonstrates higher explanatory power than Model 6, it is considered the more appropriate model.

In conclusion, for the sample including the financial crisis period, changes in IMVOL1 do predict future CDS spread changes. However, the significance of the coefficient is unstable across models, meaning the results do not strongly support the hypothesis of this study.

However, turning to Panel B, we find very encouraging results. In Model 1, when the change in IMVOL1 is used as the sole explanatory variable in the regression analysis, β_1 is 0.009, which is positive and strongly significant. The adjusted R-squared is 3.1%. Furthermore, from Model 2 to Model 6, β_1 consistently maintains its significance at the 1% or 5% level, and the magnitude of the coefficient remains stable between 0.008 and 0.012. The adjusted R-squared values also gradually increase, with Model 6 achieving an adjusted R-squared of 31.4%. This result demonstrates significantly stronger explanatory power compared to the model analyzed by Cao *et al*. (2023), which reported an explanatory power of 20.8% for the US CDS market.

Therefore, during normal periods excluding the financial crisis, it can be concluded that changes in IMVOL1 strongly predict future CDS spread changes in the Korean market. These findings are consistent with the results of Cao *et al*. (2023), which demonstrate that changes in implied volatility have cross-sectional predictive power for bond yields or CDS spread changes in the US market. Furthermore, these results support their assertion that changes in implied volatility reflect information about changes in default risk.

Table 6 shows the results of the predictive regression analysis of changes in IMVOL2 for future CDS spread changes. Panel A presents the results for the entire sample period, while Panel B shows the results for the sample period excluding the global financial crisis. The coefficients shown represent the time-series averages of the Fama-Macbeth cross-sectional regression coefficients, and the numbers in parentheses correspond to the Newey-West adjusted *t*-statistics. (*p*-value: ***<0.01, **<0.05, and *<0.10) The adj. R^2 represents the time-series average of the adjusted R-squared.

First, looking at the results in Panel A, in Model 1, when the change in IMVOL2 is used as the sole explanatory variable in the regression analysis, β_1 is 0.011, which is positive and statistically significant at the 5% significance level. The adjusted R-squared is 1.7%. In Model 3 and Model 4, when the stock return variable and the CDS percentage change variable are added, the coefficient of the change in IMVOL2, β_1, remains statistically significant at the 1% and 5% significance levels, respectively. In particular, in Model 5, when the IMVOL2 level variable and the CDS liquidity variable are controlled, β_1 remains statistically significant at the 5% significance level, and the adjusted R-squared is 29.7%, indicating a high explanatory power.

Meanwhile, in Model 2, when the IMVOL2 level variable is added to control for the effects in addition to Model 1, and in Model 6, when the IMVOL2 level variable is added to control for the effects in addition to Model 4, the significance of β_1 disappears in both models. However, like the results in Table 5, Model 6 had a lower adjusted R-squared value than Model 5, making it difficult to consider Model 6 as an appropriate model. Therefore, Model 5 can be considered the most appropriate model.

Therefore, like the conclusion regarding the change in IMVOL1 in Table 5, for the sample including the financial crisis period, changes in IMVOL2 do predict future CDS spread

Table 6. Predictability of ΔIMVOL2 for change in CDS spread

Variable	Model1	Model2	Model3	Model4	Model5	Model6
Panel A: full sample period						
Intercept	0.000	−0.001	0.000	0.001	−0.001	−0.001*
	(0.38)	(−0.74)	(0.38)	(0.93)	(−0.91)	(−1.77)
ΔIMVOL2	0.011**	0.005	0.008***	0.010**	0.006**	0.004
	(2.35)	(1.27)	(2.72)	(2.09)	(2.34)	(1.46)
IMVOL2		0.003			0.002	0.005
		(0.62)			(0.66)	(1.49)
FSR			−0.003*			
			(−1.98)			
CDSR				0.003		0.005**
				(1.66)		(2.33)
CDSLiq					0.006	
					(0.80)	
adj. R^2	0.017	0.036	0.035	0.25	0.297	0.267
Panel B: sample period excluding the global financial crisis						
Intercept	0.000	0.000	0.000	0.000	0.001	−0.001
	(0.04)	(1.08)	(-0.50)	(0.12)	(0.77)	(-1.27)
ΔIMVOL2	0.008**	0.007*	0.009**	0.007**	0.006*	0.006**
	(2.10)	(1.71)	(2.37)	(2.30)	(1.72)	(2.54)
IMVOL2		−0.002			−0.002	0.001
		(−0.81)			(−1.53)	(−0.92)
FSR			−0.002*			
			(−1.80)			
CDSR				0.003		0.003*
				(1.43)		(1.71)
CDSLiq					0.001	
					(0.15)	
adj. R^2	0.016	0.037	0.057	0.278	0.278	0.297

Source(s): The authors

changes. However, since the significance of the coefficient is unstable across models, the results do not strongly support the hypothesis of this study. Nevertheless, an important point is that the coefficient of the change in IMVOL2 shows slightly higher significance than that of the change in IMVOL1. This suggests, similarly to the interpretation of the portfolio analysis results, that the implied volatility of straddle options during the financial crisis period contains additional information about default risk.

On the other hand, looking at the results in Panel B, more interesting findings can be observed. In Model 1, when the change in IMVOL2 is used as the sole explanatory variable in the regression analysis, β_1 is 0.008, which is positive and statistically significant. The adjusted R-squared is 1.6%. Furthermore, from Model 2 to Model 6, β_1 maintains its significance at the 5% or 10% significance level, and the magnitude of the coefficient remains very stable, ranging from 0.006 to 0.009. The adjusted R-squared values also gradually increase, with Model 6 achieving an adjusted R-squared of 29.7%. Although this is slightly lower than the adjusted R-squared of 31.4% in Model 6 of Table 5, it still demonstrates high explanatory power. Therefore, during normal periods excluding the financial crisis, changes in IMVOL2 can also be considered a predictor of future CDS spread changes in the Korean market.

Taken together, for the normal periods excluding the financial crisis, models including the change in IMVOL1 show slightly higher explanatory power than those including the change in IMVOL2. In contrast, for the period including the financial crisis, models incorporating the change in IMVOL2 demonstrate slightly better predictive power of change in implied volatility than models with the change in IMVOL1.

4.3 Robustness check

In the previous empirical analysis, implied volatility from stock options is calculated using only near-the-money options with maturities of 180 days or more and strike prices ranging from 80% to 120% of the stock price. In practice, it is ideal to extract implied volatility from at-the-money options, but there is an issue of not being able to secure sufficient data in such cases. Moreover, in case that there are multiple implied volatilities across different strike prices on the same date, this study calculates the equal-weighted average implied volatility by assigning equal weights to each strike price. However, using near-the-money options to calculate an equal-weighted average may expose the analysis to the volatility smile issue, where implied volatilities vary across strike prices.

Thereby, due to the potential for measurement errors in calculating implied volatility, only options with strike prices between 90% and 110% of the stock price, which are closer to at-the-money, will be used to extract implied volatility. The previous empirical analysis will be re-executed using these options. Further, since the predictive power is stronger in the sample excluding the financial crisis period compared to the sample including the financial crisis period, this robustness check will be conducted using the sample that excludes the financial crisis period.

Table 7 shows the results of the predictive regression analysis of implied volatility changes using options that are closer to at-the-money. Panel A consists of models that include the change in IMVOL1, while Panel B consists of models that include the change in IMVOL2.

Table 7. Robustness check

Variable	Model1	Model2	Model3	Model4	Model5	Model6
Panel A: models with Δ IMVOL1						
Intercept	0.000	−0.003	0.000	0.000	−0.004	−0.004
	(−0.13)	(−0.80)	(−0.05)	(−0.12)	(−1.08)	(−1.08)
ΔIMVOL1	0.014*	0.021***	0.017**	0.013**	0.019***	0.020***
	(1.96)	(3.08)	(2.59)	(2.21)	(3.22)	(3.81)
IMVOL1		0.009			0.01	0.011
		(0.74)			(0.89)	(0.99)
FSR			−0.003			
			(−1.18)			
CDSR				0.005*		0.006*
				(1.72)		(1.88)
CDSLiq					0.007	
					(1.02)	
adj. R^2	0.009	−0.002	0.096	0.290	0.358	0.298
Panel B: models with Δ IMVOL2						
Intercept	0.000	0.001	0.000	0.000	0.000	−0.001
	(−0.07)	(−1.67)	(−0.32)	(−0.17)	(−0.22)	(−1.17)
ΔIMVOL2	0.014*	0.011*	0.015**	0.010**	0.009**	0.006***
	(1.80)	(1.83)	(2.05)	(2.02)	(2.04)	(2.70)
IMVOL2		−0.002			−0.002	0.002
		(−1.07)			(−1.05)	(0.91)
FSR			−0.003*			
			(−1.88)			
CDSR				0.002		0.002
				(0.94)		(1.20)
CDSLiq					0.005	
					(0.68)	
adj. R^2	0.031	0.044	0.103	0.281	0.280	0.274

Source(s): The authors

First, looking at Panel A, it can be observed that across all models, β_1 is positive and maintains statistical significance. The magnitude of the coefficient remains stable, ranging from 0.013 to 0.02. In particular, the adjusted R-squared for Model 5 is 35.8%, which demonstrates significantly higher explanatory power compared to the model that used IMVOL1 extracted from near-the-money options. (The adjusted R-squared of Model 5 in Panel B of Table 5 is 30.6%.)

Looking at the results in Panel B, it can be observed that from Model 1 to Model 6, β_1 is positive and statistically significant. The magnitude of the coefficient remains generally stable, ranging from 0.006 to 0.015. The model with the largest adjusted R-squared is Model 4, with a value of 28.1%, which is like the results obtained using near-the-money options. However, when compared to the results in Panel B of Table 6, the range of changes in the coefficient values across models is relatively larger, suggesting a slight decrease in stability. Nonetheless, it is confirmed that statistical significance increases.

In the end, despite the smaller sample size, the robustness check is conducted using options closer to at-the-money to improve the accuracy of the implied volatility calculation. The results still support the hypothesis that changes in stock option implied volatility predict future CDS spread changes in the Korean market.

5. Conclusion

This study aims to verify whether changes in the implied volatility of individual stock options in the Korean market reflect information about default risk and have cross-sectional predictive power for future changes in CDS spreads. The reason for verifying CDS spreads instead of bond yields is that CDS is more directly related to default risk than bonds, and previous research has reported that the CDS market reacts more quickly to default risk information than the bond market.

The main results of the investigation conducted on 19 Korean companies for which both 5-year CDS spread data and OTC stock options data are available simultaneously from April 2005 to October 2012 are as follows: First, when buying the portfolio with the largest increase in implied volatility and selling the portfolio with the largest decrease, and reconstructing monthly, the average value of the change in CDS spreads for the following month is significantly positive. Second, the cross-sectional predictive regression analysis results show that the coefficient for changes in implied volatility is significant in most models, and the magnitude of the coefficients remains generally stable regardless of control variables, confirming the cross-sectional predictive power for future changes in CDS spreads. These findings are consistent with the argument of Cao *et al*. (2023) that increases in implied volatility reflect information about heightened default risk due to corporate uncertainty shocks. Third, in a sample that includes the financial crisis period, the implied volatility change variable, calculated by incorporating the implied volatility of straddle options—unlike the methodology used in previous studies—demonstrates stronger predictive power. This suggests that the implied volatility of straddle options contains additional information about default risk during global financial crisis.

The findings of this study, which suggest that changes in the implied volatility of individual stock options provide significant information about default risk and future CDS spread variations, offer a new dimension to risk management strategies from a practical perspective. Specifically, the changes in implied volatility can be utilized to detect and manage corporate default risk at an early stage and to more accurately assess the credit risk of individual companies. This can serve as a foundation for building more detailed credit evaluation models. From a policy perspective, considering that changes in implied volatility quickly reflect shifts in credit risk, it can be used as a tool to monitor risks in real-time in the financial market by linking it with CDS spreads. Notably, during rapidly changing periods such as financial crises, changes in implied volatility of straddle options can exhibit greater predictive power. Therefore, it is possible to establish a policy framework that incorporates implied volatility indicators into crisis response policies.

This study has the following limitations. First, the number of firms analyzed is very small, and the time series data for each company varies, making it difficult to confirm strong predictive power in portfolio analysis. This can be attributed to the low trading volumes and the limited variety of underlying entities in the CDS market and the individual stock options market in Korea. Second, the exchange market for individual stock options is not well-developed, with most individual stock options being traded OTC in Korea. This creates challenges in data collection, leading the analysis to rely heavily on historical data. It is hoped that both derivative markets will develop further in the future, allowing us to obtain analysis results based on more recent data for a broader set of firms.

Notes

1. Cao *et al*. (2023) use the average implied volatility change of call options and put options as the implied volatility change variable to examine its predictive power for future stock returns, but they find that it does not predict these returns.
2. When calculating IMVOL2, if the quotes or traded prices for straddle options are not available on certain dates, the average of the implied volatilities of call options and put options is used as a substitute.
3. This formula is the same as the one for the Credit Protection Return (CPR) in Park and Park (2024). The paper defines the CPR as the CDS returns. Accordingly, the CDS percentage rate represents the yield obtained when trading a CDS.
4. Calculations are restricted to cases where the number of observations in the cross-sectional regression analysis per month is at least 6.
5. We generate the time-series average of the cross-sectional correlations of the independent variables. In unreported results, ΔIMVOL1 is moderately correlated with IMVOL1, with a correlation of 0.47, and ΔIMVOL2 is moderately correlated with IMVOL2, with a correlation of 0.46. These results suggest that they may share a common component. Therefore, we aim to examine whether the change in implied volatility still provides distinct information from the implied volatility level, despite the moderate correlations, by controlling for the implied volatility level.

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