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The Term Structure of Credit Default Swap Spreads and the Cross Section of Options Returns

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ABSTRACT

This paper, using the natural logarithmic form credit default swap (log CDS) slope, examines the variation in cross-sectional 1-month ATM delta-hedged straddle returns. Our analysis reveals that the log CDS slope significantly and positively predicts these returns, even when accounting for several key volatility mispricing factors. Further investigation shows that this predictive relationship exhibits a strong time-varying pattern, closely linked to market conditions. In contrast, the relationship between notable volatility mispricing factors and straddle returns remains relatively stable over time. Constructing a long-short quintile portfolio on straddle options confirms that trading performance improves when the past 12-month market return is at a historically lower level, market volatility is at a historically higher level, and the VIX is elevated. Log CDS slope, as a proxy for excess jump risk premium, significantly predicts delta-hedged option returns during periods of high volatility.

JEL Classification: C13, C51, G12, G13

1 | Introduction

The credit default swap (CDS) spread is a key indicator of credit risk, reflecting the financial health of firms. Single-name CDS contracts attract greater attention and liquidity during volatile periods as investors seek credit risk protection. CDS index further captures the market's attitude toward systematic credit risk. As Carr and Wu (2010) build a direct relationship between the CDS spread and put option, it shows there exists a one-by-one mapping between CDS spread and option implied volatility (OIV). Further, Vasquez (2017) finds that the implied volatility slope ($IV_{1m} - IV_{12m}$) can significantly and positively predict the delta-hedged straddle return, after controlling for several option return predictors. This raises the question of whether the CDS slope (CDS 5-year spread–CDS 1-year spread) can predict the delta-hedged straddle return, as it functions like CDS-based implied volatility slope with an additional credit risk component.

The term structure of CDS spread, measured by the difference between 5-year and 1-year single-name CDS spreads, reflects the trend in credit risk. We use the logarithmic version as the simple difference is largely influenced by the level or size of the CDS spreads. In contrast, the log CDS slope is primarily driven by credit risk trend, allowing for more effective cross-sectional comparisons. Han et al. (2017) show that the CDS slope has a negative relationship with stock returns. Their findings suggest that firms with higher CDS slopes tend to have lower future stock returns from a cross-sectional perspective. This indicates that firms with higher CDS slopes are likely to experience greater future volatility due to the leverage effect, where lower stock prices lead to higher stock volatility. However, delta-hedged option returns are driven not by the level of volatility alone but by volatility mispricing, defined as the difference between implied volatility and future realized volatility. Goyal and Saretto (2009) find that the difference between 1-month at-the-money (ATM) implied volatility and 1-year historical volatility has predictive power on the return of straddle and delta-hedged call. They use 1-year historical volatility (HV_{12m}) as a break-even volatility for future 1-month volatility (FV_{1m}). Academics tend to use a difference concept (i.e., $IV_{1m} - HV_{12m}$), to represent the overpricing or underpricing at cross-section (Goyal and Saretto 2009).

We investigate the relationship between the log CDS slope and potential candidate factors that could explain cross-sectional delta-hedged option returns. Our analysis confirms that none of these factors account for the log CDS slope with an R^2 exceeding 10%. Additionally, we examine the link between the log CDS slope and cross-sectional delta-hedged 1-month ATM straddle returns. We find that selling stock options with a higher log CDS slope tends to yield, on average, higher returns over the full sample period. To delve deeper, we analyze its performance across different sample periods and observe that the returns vary over time. Secondly, we investigate whether other factors can explain this pattern through an unconditional option return analysis. Using the Fama-MacBeth regression, we incorporate a list of candidate factors alongside the log CDS slope to examine the cross-sectional variation in delta-hedged option returns. Our results confirm that none of the other factors can eliminate the predictive power of the log CDS slope for delta-hedged option returns. Third, we assess the rolling performance of a long-short trading strategy based on options sorted by log CDS slope and find that the predictive relationship is time-varying. Lastly, we conduct a conditional analysis to explore this forecasting relationship under different market conditions. We segment the sample into several sub-samples defined by market condition proxies, including the past 1-year market return, past 1-year market-level historical volatility, and the VIX. The analysis reveals that the predictive relationship is stronger and more positive when the past 1-year market return is at historically lower levels, the past 1-year market volatility is at historically higher levels, and the VIX is elevated. In summary, all empirical findings indicate that the log CDS slope is a robust and significant predictor of delta-hedged straddle returns in the cross-section, particularly during periods of heightened market volatility. This paper makes two key contributions. First, it introduces the log CDS slope as a novel predictor of delta-hedged straddle returns, filling a critical gap in understanding the general information spillover between the CDS and option markets. Second, it conducts a conditional asset pricing test, demonstrating that the predictive power of the log CDS slope on cross-sectional delta-hedged option returns strengthens as market volatility rises. This finding sheds light on the conditional dynamics of information spillover between the CDS and option markets.

Our findings on the conditional (time-varying) relationship align with the existing literature. For instance, Pan (2002) performs a joint estimation of stock returns and option prices to identify the jump and volatility risk premiums embedded in option pricing. Her study, focusing on 1-month SPX options with market volatility targeted at 10% and decomposing risk premiums into jump and volatility components, reveals that the jump risk premium in out-of-the money (OTM) puts contributes approximately 80% of the total risk premium. In contrast, for ATM options, the contribution of the jump risk premium decreases to 55%. For instance, when market volatility increases from 10% to 50%, the jump risk premium for 1-month ATM options more than triples, while the volatility risk premium increases only marginally. Using the URC (Unit Recovery Claim) theory proposed by Carr and Wu (2011), the CDS spread is shown to have a direct one-to-one mapping with deep OTM American put option, and consequently, implied volatility. Thus, the log CDS slope can be interpreted as the difference between the implied volatility of an OTM put and its breakeven volatility. According to Pan (2002), the jump risk premium predominantly drives the risk premium of OTM puts, positioning the log CDS slope as a proxy for excess jump risk premium. Furthermore, as Pan (2002) notes, when market volatility is elevated, the jump risk premium dominates the total risk premium for ATM options, becoming the primary driver of delta-hedged ATM option returns. Therefore, our finding that the log CDS slope exhibits stronger predictive power for delta-hedged option returns in volatile markets aligns well with the established literature.

The paper structure is designed as follows. Literature review explains the paper's motivation and its connection with existing literature. The third chapter is methodology, explaining the construction for each variable. Data is the following chapter explaining the data source and provides the summary statistics. The fifth chapter talks about the unconditional delta-hedged option return, by using log CDS slope as the trading signal at cross-section and examine its robustness. The sixth chapter expands to the conditional delta-hedged option return, depending in the market conditions. The final chapter makes a conclusion.

2 | Literature Review

The empirical relationship exploring how CDS market impacts the stock or option market, especially through stock returns and stock option volatility, has been recognized in the academic community. Among the research for information spillover between different markets, our paper contributes to the information spillover from CDS market to option market, especially the delta-hedged option return.

The determination of CDS spreads is commonly approached through two methodologies: structural models and reduced-form models. Structural models are inherently linked to the option pricing frameworks introduced by Merton (1974) by assuming the firm asset value fellows geometric Brownian motion and considers the firm's debt and equity as contingent claims dependent on the value of its assets. These models operate on the premise that CDS spreads are fundamentally influenced by the default risk of the reference entity, with adjustments to the risk premium driven by changes in the entity's probability of default. Also related to our work is a much longer list of studies on CDS spread and credit risk factors: Di Cesare and Guazzarotti (2010), Annaert et al. (2013), Galil et al. (2014), and Bai and Wu (2016). In contrast, reduced-form models, often employing event study methodologies, focus on analyzing the impact of random shocks on CDS spreads. While structural models assume a deterministic relationship between CDS spreads and factors affecting firm value and default probabilities, reduced-form models consider defaults as outcomes of external stochastic events. Merton (1976) acknowledges the direct influence of corporate default on stock price dynamics, assuming that the stock price abruptly drops to zero and remains at that level upon the occurrence of a default event. Although reduced-form models offer simplicity, they have faced criticism for lacking a robust economic foundation to justify their findings Alexopoulou et al. (2009). Hence, Carr and Wu (2010) propose a theoretical connection between CDS market and option market. They build a theoretical connection between CDS spread and default-level Deep-OTM put option. They also confirm, CDS spread variation is better explained by the variation of Deep OTM put's implied volatility instead of ATM volatilities. Specifically, Zhang et al. (2009) find that CDS spread is highly influenced by idiosyncratic volatility risk premium estimated from high-frequency stock trading data. Variance risk is confirmed to account for near 50% variation in CDS spread while jump risk only accounts for about 19% of the CDS spread variations. Furthermore, Wang et al. (2013) investigate whether variance risk premium will influence equity CDS. The variance risk premium, the difference with implied volatility and expected future volatility, is strongly related to CDS. Consequently, much of the research on the factors influencing CDS spreads has concentrated on structural models, which utilize firm-specific and market-specific variables to provide more economically grounded explanations for the observed spread variations.

In examining the information spillover effects from the CDS market to the stock market, a growing body of research has demonstrated the predictive capacity of CDS spreads for stock returns (Amihud 2002; Garlappi et al. 2008; Chava and Purnanandam 2010). Traders with access to inside information tend to prefer trading in stocks rather than CDS contracts due to the lower transaction costs associated with stock trading (Hilscher et al. 2015). Friewald et al. (2014) investigated the relationship between stock returns and credit risk, as conceptualized in the Merton (1974) model, finding that a higher credit risk premium estimated from the CDS market increases expected stock returns. Their findings confirm a positive relationship between credit risk and stock returns. Similarly, Avramov et al. (2009) argued that firms with higher credit ratings tend to offer higher stock returns. In addition to the CDS level, the slope of the CDS term structure also exhibits predictive power for future stock returns. Meng et al. (2009) identified a negative correlation between the CDS slope and stock returns, suggesting that the CDS slope can serve as an additional predictor for future stock performance. Fung et al. (2008) further supported this notion, showing that information embedded in the CDS market, reflected in the CDS slope, can be used to forecast stock returns. Han and Zhou (2011) analyzed the relationship between the slope of the CDS term structure and the expected returns of corresponding firm stocks, finding that a steeply rising CDS slope is associated with negative abnormal stock returns, while a mildly upward-sloping CDS term structure corresponds to positive abnormal stock returns. Moreover, these abnormal returns appear to persist for up to 6 months. In the context of sovereign CDS markets, Calice et al. (2015) examined the term structure of CDS spreads (measured by the difference between 10-year and 5-year CDS spreads) across five European sovereign entities. Their findings align with studies on corporate single-name CDS term premiums, revealing that the slope of the sovereign CDS yield curve is influenced by local stock market returns, investor risk aversion, and market liquidity. Additionally, they observed that the sensitivity of the slope to sovereign CDS term structure varies across market regimes, with its impact magnified by up to tenfold during periods of heightened market volatility. These results highlight the dynamic relationship between CDS term structures and stock market performance, underscoring the nuanced role of market conditions in shaping these interactions.

Further research has delved into the intricate interdependence between the stock and CDS markets. Han et al. (2017) demonstrated that these two markets are closely interconnected, with sustained growth in the stock market contributing to higher-rated CDS spreads. Conversely, activity within the CDS market has been shown to influence stock market volatility (Forte and Pena 2009). Additionally, Berndt and Obreja (2010) identified catastrophe risk as a critical determinant of CDS returns, explaining over half of their variability, particularly within European economic entities. These findings underscore the bidirectional relationship between the two markets and the central role of macroeconomic risks in shaping CDS dynamics.

3 | Methodology

The difference between 5-year CDS spread (CDS_{5y}) and 1-year CDS spread (CDS_{1y}) are selected for constructing CDS slope, following the previous literature. The CDS slope can be interpreted as the default intensity trend in the future. The high-quality and broad CDS data allow us to explore the information of credit risk at both cross-section and time-series. Some scholars extract debt information from company balance sheets or credit ratings given by some credit rating companies. Those studies are subject to be affected by maturity clustering. Specifically, companies with high credit rating tend to issue long-term bonds, which can lead to the credit spreads with different maturities clustered together. Furthermore, as one single firm will issue bonds with varied maturities, the liquidity for firm bond becomes an issue. Thus, CDS contract becomes a much cleaner proxy for credit risk instead of bond-implied credit spread. In addition, all CDS contracts are selected with Modified Restructuring clause (MR clause), to reduce the impact of changes in recovery rate.

CDS slope is just the difference between two CDS spreads, while its natural logarithmic form has better distribution features, with skewness and kurtosis more approaching normal distribution,

$$CDS\ Slope = S_{5y} - S_{1y}, \tag{1}$$

$$\ln(CDS\ Slope) = \ln\left(\frac{S_{5y}}{S_{1y}}\right). \tag{2}$$

Similar to the constructive way of CDS slope, Goyal and Saretto (2009) propose a volatility mispricing proxy (IV-HV Slope) as the difference between 30-day ATM option implied volatility (IV_{1m}^{ATM}) and 1-year historical volatility (HV_{12m}), where IV_{1m}^{ATM} is the average of 30-day ATM put option implied volatility and 30-day ATM call option implied volatility, $IV_{1m}^{ATM} = \left(IV_{1m}^{Call} + IV_{1m}^{Put}\right)/2$. Vasquez (2017) proposes the IV Slope, which is the difference between IV_{1m}^{ATM} and IV_{12m}^{ATM}.

$$IV - HV\ Slope = IV_{1m}^{ATM} - HV_{12m}, \tag{3}$$

$$IV\ Slope = IV_{1m}^{ATM} - IV_{12m}^{ATM}. \tag{4}$$

Previous research has measured the option-implied jump, as the difference between ATM call and ATM put option on the same underlying stock (Bali and Hovakimian 2009; Cremers and Weinbaum 2010; Xing et al. 2010). The jump, they proposed, carries significant information regarding future equity returns. Investors with privileged information tend to purchase call (put) options, resulting in upward pressure on call (put) option prices (as indicated by implied volatilities) relative to put (call) option. As this nonpublic information gradually permeates the equity markets, the prices of the underlying stocks adjust upwards. Consequently, a jump is expected to serve as a negative indicator of future returns for the underlying stocks, the higher, the more negative return in future.

$$Jump = IV_{1m}^{Put} - IV_{1m}^{Call}. \tag{5}$$

A negative jump is commonly interpreted as a bullish signal, while a positive jump is associated with bearish expectations regarding the underlying stock. We adopt the jump as a tool to detect demand pressures in the equity option market driven by informed trading.

The volatility of implied volatility, $\sigma_{IV_{1m}}$, is calculated to capture the uncertainty of expected volatility in the past 1 month, just the standard deviation of IV_{1m} in past 1 month.

$$\sigma_{IV_{1m}} = \sqrt{\frac{1}{30}\sum_{t-1}^{t-30}(IV_{1m,i} - \bar{IV}_{1m})^2}, \text{ where } i \in [1, 2, \dots 30]. \tag{6}$$

Essentially, it reflects the fluctuations in volatility, capturing the degree of uncertainty or risk regarding the changes in the option prices. This measure is crucial as it provides insights into market sentiment and the dynamic nature of volatility expectations over a short-term horizon, serving as a proxy for the market's anticipated risk. $\sigma_{IV_{1m}}$ is particularly informative for option traders and risk managers, as it reveals periods of heightened uncertainty that could influence both hedging strategies and speculative activities in the option market.

4 | Data

Our data set spans a period of 239 months, with the final month reserved for predictive analysis. This time frame encompasses the period from January 2002 to December 2021. All data, including CDS, option and stock information are collected from WRDS database. To ensure a broad and representative sample, we impose a requisite of minimum efficient filters. First, common equities traded in the three major US exchanges are selected, and firms must have full return observations to calculate HV_{12m} in past 1 year. Secondly, a security must have valid 1-year and 5-year CDS spreads, of which the CDS contracts are denominated in U.S. dollars and meet the MR-clause.

The details of cleaning option data is illustrated as follows. Firstly, for the 1-month ATM option contracts, the basic requirements are as follows: we restrict our observation date as 30 days before the option's monthly settlement date (normally third Friday of each month), and our trading day is 4 weeks' ago Wednesday to ensure that the option's maturity is purely 30 calendar days; option contracts must meet no arbitrage bounds, such as $0 < bid < ask$, and valid implied volatility; the moneyness (the ratio of strike price, K to stock price, S) of ATM option are closest to 1, and within the range of [0.95, 1.05]; thirdly, one single firm at each trading day has at least 3 valid straddle with different strikes for liquidity consideration; stock price is above $5 at observation date, which can reduce the impact of bid-ask spread on return calculation and further volatility estimation. We use the information in selected option contracts to build the volatility mispricing measure, $IV_{1m} - HV_{12m}$. Secondly, for the ATM-IV, Volatility surface in Option Metrics provides smoothed implied volatility for companies with specific delta and constant maturity. We use the information in volatility surface to build the jump, $IV_{1m}^{Put} - IV_{1m}^{Call}$ and Vasques' volatility mispricing measure, $IV_{1m} - IV_{12m}$. Thirdly, delta-hedged option return is the delta-hedged P&L from the seller's perspective divided by the principle, the option price at trading day, where $P\,\&\,L = O_t \cdot e^{r(T-t)} - O_T + \Delta_t(S_T - S_t \cdot e^{r(T-t)})$. Finally, the data set has 713 companies with total 63,661 month-firm observations over 20 years.

Figure 1 illustrates the number of selected firm per month. It reports the number of companies at each month in the past 20 years: the firm number begins around 150, reaches the top around 400 during 2008–2009 financial crisis, and then decreases to around 250 to 300 since 2010.

Table 1 reports the time-series average of the cross-sectional summary statistics across all companies and over the whole time period. This data set is multifaceted, encompassing a range of firm characteristics. First, CDS_{5y} has a mean value of 0.015, coupled with a standard deviation of 0.029, where its 5th and 95th percentiles stand at 0.002 and 0.049. In parallel, CDS_{1y} exhibits a mean of 0.008 and a standard deviation of 0.036, where the 5th and 95th percentiles are 0 and 0.03. Hence, CDS_{1y} tends to have smaller magnitude but larger variation compared with CDS_{5y}. The significant difference in magnitude and variation between CDS_{5y} and CDS_{1y} results in the variation of CDS slope and log CDS slope, where the mean of CDS slope is largely influenced by the general CDS spread level. Hence, the log CDS slope becomes a more cross-section comparable ratio to differentiate the credit default trend. Secondly, HV_{12m} has a larger mean and standard deviation (34.5%, 19.1%) compared with both IV_{1m} (33.8%, 18.5%) and IV_{12m} (32.3%, 13.3%), because HV_{12m} generally includes four earnings announcement events and is a realized value instead of an expected one with more

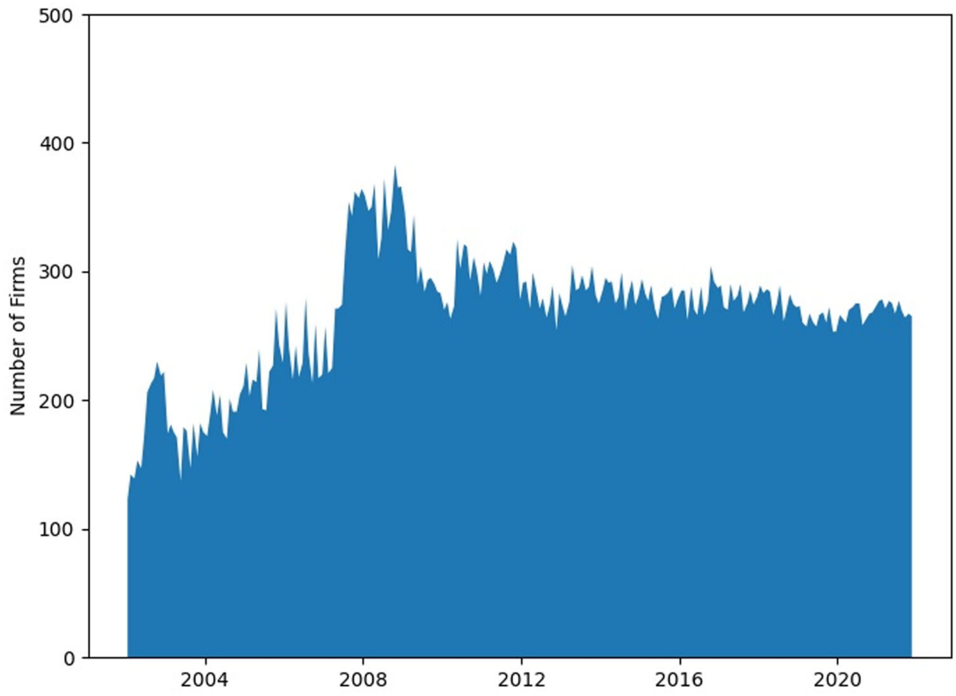


FIGURE 1 | Number of selected stocks per month. Figure shows the number of selected companies every month in the sample from January 2002 to December 2021. Due to the availability of CDS data, the number of selected companies reaches the highest less than 400 during 2008–2009 financial crisis period, and remains stable around 250–300. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Summary statistics across U.S. Market Listed Firms.

Variable	Mean	Std	5%	10%	25%	50%	75%	90%	95%	Total
# of firms										713
# of observation										63,661
# of month										239
CDS_{5y}	0.015	0.029	0.002	0.003	0.004	0.008	0.016	0.033	0.049	
CDS_{1y}	0.008	0.036	0.000	0.001	0.001	0.002	0.006	0.016	0.030	
HV_{12m}	0.345	0.191	0.158	0.177	0.220	0.295	0.409	0.564	0.706	
IV_{1m}	0.338	0.185	0.158	0.177	0.220	0.290	0.397	0.542	0.676	
IV_{12m}	0.323	0.133	0.179	0.196	0.234	0.290	0.375	0.485	0.580	
Jump	0.002	0.033	−0.024	−0.016	−0.007	0.001	0.009	0.019	0.030	
ln (size)	9.600	1.328	7.394	7.858	8.693	9.622	10.492	11.296	11.862	
CDS slope	0.007	0.015	0.001	0.001	0.002	0.004	0.008	0.017	0.025	
$IV_{1m} - HV_{12m}$	−0.007	0.132	−0.192	−0.120	−0.046	−0.002	0.040	0.093	0.146	
$IV_{1m} - IV_{12m}$	0.015	0.077	−0.056	−0.044	−0.026	0.001	0.032	0.081	0.131	
ln(CDS slope)	1.147	0.620	0.074	0.246	0.660	1.247	1.618	1.898	2.055	
$\ln(IV_{1m}/HV_{12m})$	−0.016	0.257	−0.451	−0.329	−0.162	−0.008	0.143	0.281	0.371	
$\ln(IV_{1m}/IV_{12m})$	0.004	0.160	−0.238	−0.187	−0.101	−0.003	0.095	0.195	0.276	
Straddle ret	0.027	0.883	−1.399	−0.967	−0.349	0.209	0.628	0.860	0.935	
Straddle ret(DH)	0.029	0.870	−1.349	−0.898	−0.310	0.208	0.595	0.821	0.898	
$\sigma_{IV_{1m}}$	0.031	0.035	0.008	0.010	0.014	0.022	0.035	0.056	0.080	

Note: Entries report the time-series average of cross-sectional summary statistics of several volatility and CDS-related variables, covering the period from January 2002 to December 2021. # of firms is number of companies; # of month is number of months; # of observations is the total number of company-month observations.

noise. The smaller magnitude of IV_{1m} compared with IV_{12m} matches the general sense: implied volatility term structure for stock-level is downward-sloping, while implied volatility term structure for index-level is upward-sloping due to notable systematic variance risk premium (Wu and Xu 2024). The volatility of implied volatility, $\sigma_{IV_{1m}}$, means the daily IV_{1m} can moves with deviation from −6.2% to 6.2% at the 95% confidence level, on average. And IV_{1m} is also varying a lot at cross-section, from 1% at the 10% position to 5.6% at 90% position. For all the volatility mispricing measures, either the normal version or log version all exists a strong cross-sectional variation. Thirdly, for option return, 1-month ATM straddle return has a similar magnitude with that of 1-month delta-hedged ATM straddle return, with 2.7% and 2.9% seperately. It indicates, the selected ATM straddles contain only a small amount of delta exposures, of which by applying further delta-hedging can only reduce a quite small amount of stock return risk.

Figure 2 plots the time-series of the cross-sectional average CDS spread together with volatilities of all companies spanning the whole period from January 2002 to December 2021. Panel A reveals a striking pattern of CDS spread over time, with notable fluctuations that align with key events in the global financial landscape. In parallel with the credit crisis during 2008-2009, both the CDS_{1y} and CDS_{5y} escalated dramatically, reaching a peak of averagely 4.5%. When comparing CDS_{1y} with CDS_{5y}, an intriguing pattern emerges: during the financial crisis, the mean values of CDS_{1y} and CDS_{5y} converged, suggesting that investors view short-term default risk as high as long-term default risk. During normal periods, CDS_{1y} is typically lower than the CDS_{5y},

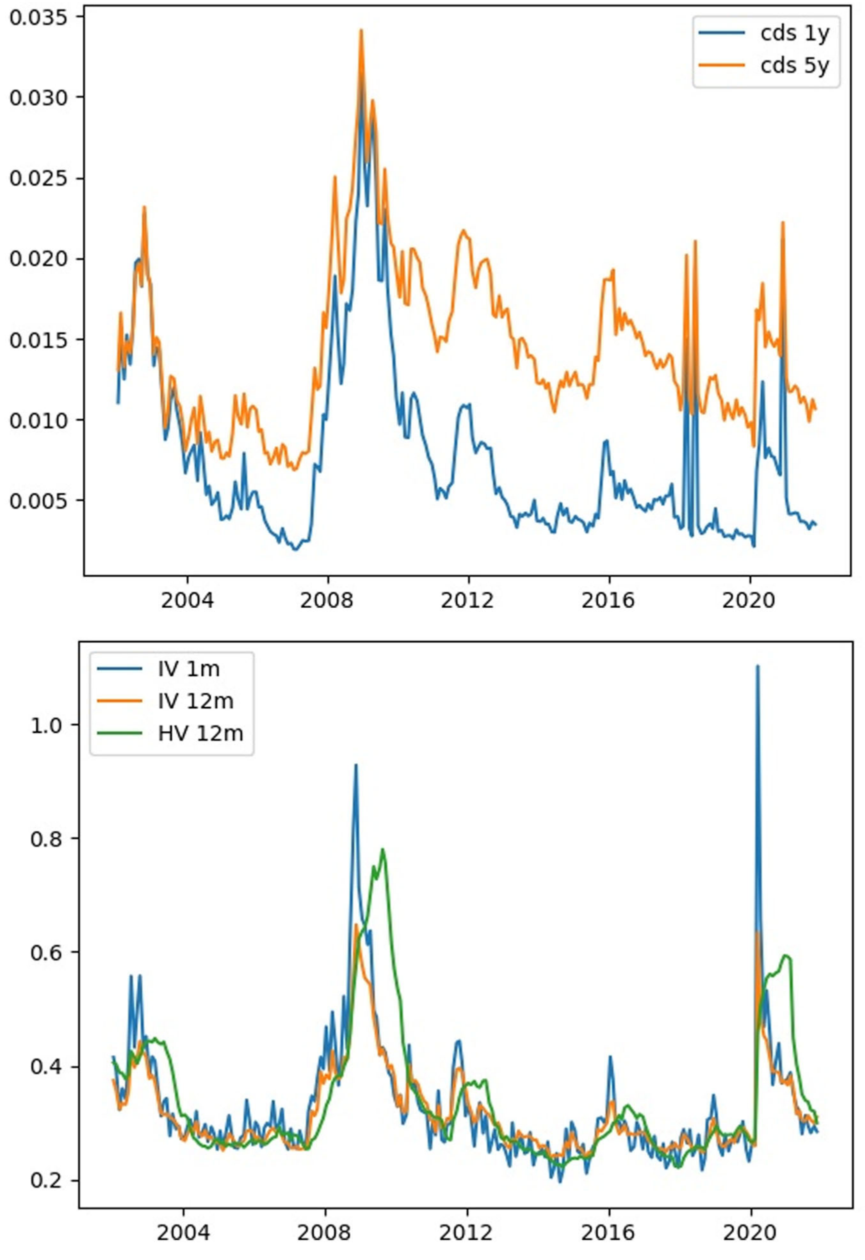


FIGURE 2 | Cross-sectional average volatilities and CDS spreads per month. Figure provides a compelling visual representation of the average volatilities and CDS spreads among all selected companies at each month, spanning a period from January 2002 to December 2021. [Color figure can be viewed at wileyonlinelibrary.com]

with magnitude of 0.07% on average. Panel B of Figure 2 reveals a similar pattern among volatilities: average volatilities tend to spike during crisis periods, ranging from 0.8 to 1.2, but otherwise, remain stable around 0.3. Hence, at the aggregate level, CDS comoves with volatility.

Table 2 reports the time-series average of cross-sectional correlation matrix for each pair of variables. The key focus is the correlation between delta-hedged straddle return and other variables. The general results show that a firm with smaller size tends to have higher volatility and CDS spread, and have a negative delta-hedged option return at cross-section: this also matches the variance risk premium theory that, selling index-based option generally make money, thus selling the option from the firms more close to market, the more money investors will get (Wu and Xu 2024). Moreover, the volatility mispricing measures, like $IV_{1m} - HV_{12m}$ and $IV_{1m} - IV_{12m}$, have strong positive relationships with the delta-hedged option return in the full sample. At the same time, our proposed log CDS slope is also positively related to the delta-hedged straddle return, while raw CDS slope is not.

5 | Unconditional Empirical Test

In this section, we examine the forecasting relationship between delta-hedged option return and log CDS slope within several dimensions. Firstly, we explore whether the forecasting power of CDS slope is determined by some notable volatility mispricing factors. Secondly, we explore the trading performance on delta-hedged option return sorted by log CDS slope in different sample periods to verify its robustness. Thirdly, we perform the Fama-Macbeth regression on delta-hedged option return to analyze the risk factor premium. Finally, we show the cumulative option return over the whole sample horizon to indicate the time-varying predicting power of log CDS slope.

5.1 | Determinants of Log CDS Slope

The reason why we use the log CDS slope instead of CDS slope, starts from the Table 1: CDS slope is mainly driven by the CDS level. CDS slope does not de-mean its own credit level, while log CDS slope has already done the de-mean operation and hence becomes a more comparable proxy at cross-section to represent the credit risk trend for future. Hence, at cross-section, CDS slope becomes a proxy like size or CDS level, of which smaller firms tends to have a higher CDS level, hence a higher CDS slope. This is consistent with our findings in Table 2: the average correlation between ln(Size) and CDS slope is −0.4, while that between ln(Size) and log CDS slope is only 0.11.

Table 3 reports the time-series average of the cross-sectional regression between log CDS slope and other controlling variables. According to the results in first three regressions, we find, log CDS slope is negatively explained by several volatilities: IV_{1m}, IV_{12m}, and HV_{12m}, where the coefficients are −0.71, −0.89 and −0.66 separately at 1% significance level. Log CDS slope is negatively determined by the different volatilities, but the explained adjusted R^2 is only limited up to 9%. Further, both $\sigma_{IV_{1m}}$ and Jump measure are negatively related to log CDS slope, but with explained adjusted R^2 like 5% and 1% separately. The key focus is how volatility mispricing measures explain the variation of log CDS slope. We find log CDS spread is still negatively related with these two volatility mispricing measures, with coefficients −0.85 and −0.30 separately for $IV_{1m} - IV_{12m}$ and $IV_{1m} - HV_{12m}$. Apparently, log CDS slope, thought as CDS-based IV slope, is more related to IV slope instead of IV-HV slope, from both theoretical and empirical connection. However, either $IV_{1m} - IV_{12m}$ or $IV_{1m} - HV_{12m}$ can only explain a small amount of variation of log CDS slope at cross-section, around 3% and 2% adjusted R^2 separately.

In summary, the findings highlight log CDS slope, as a CDS-based IV slope, is negatively related to different volatility level measures and traditional volatility mispricing measures, but all of them cannot explain a large amount of cross-sectional variation on log CDS slope.

5.2 | Option Portfolio Return Sorted by Log CDS Slope

Similar to Goyal and Saretto (2009), our research interest is to explore the predicting power of log CDS slope on option return at cross-section. We select four kinds of option return into portfolio analysis, including delta-hedged 1-month ATM call, delta-hedged 1-month ATM put, 1-month ATM straddle, and delta-hedged 1-month ATM straddle. We further decompose the whole samples into several sub-samples, by considering the settings in Han et al. (2017).

Among each sub-sample, we sort firms into five portfolios based on firm-level log CDS slope at each trading day. The number of target portfolio is set as five, by considering the number of monthly selected firm ranged only from 150 to 400 due to the availability of CDS data while Goyal and Saretto (2009) has monthly observations averagely more than 700 firms by using decile portfolios. At each trading day with monthly frequency, we calculate the simple average of each option return within the portfolio over next 1 month as the corresponding portfolio's return: portfolio 1 means the names with lowest quintile log CDS slope, while portfolio 5 means the names with highest quintile log CDS slope. Then, the long-short trading strategy is to buy the portfolio 5 and sell the portfolio 1. Along the whole time period, we calculate the time-series statistics on each portfolio's monthly return.

Table 4 reports trading performance of long-short strategy from 2002 to 2012, consistent with the Han Bing's Sample. By sorting based on log CDS slope, the portfolio return increases with increasing the log CDS slope: portfolio 5 has much better performance than portfolio 1. This pattern is persistent along all four option returns. The slightly higher return in long-short on put than that on call matches the general sense: put is sold more expensive than call, which is 5.13% and 4.45% separately. After taking additional delta-hedging on straddle, the long-short strategy will slighly decreases from 4.79% to 3.97%.

Table 5 reports trading performance of long-short strategy from 2002 to 2012, consistent with the Han Bing's Sample, but without 2008–2009 crisis period. The reason is to test its

TABLE 2 | Time-series average of cross-sectional correlation matrix.

	CDS_{5y}	CDS_{1y}	HV_{12m}	IV_{1m}	IV_{12m}	Jump	ln(size)	CDS Slope	IV_{1m} $-HV_{12m}$	IV_{1m} $-IV_{12m}$	ln(CDS Slope)	$ln(IV_{1m}$ $/HV_{12m})$	$ln(IV_{1m}$ $/IV_{12m})$	Straddle ret	Straddle ret (DH)	$\sigma_{IV_{1m}}$
CDS_{5y}																
CDS_{1y}	0.91 (***)															
HV_{12m}	0.63 (***)	0.54 (***)														
IV_{1m}	0.67 (***)	0.58 (***)	0.87 (***)													
IV_{12m}	0.7 (***)	0.61 (***)	0.91 (***)	0.94 (***)												
Jump	0.19 (***)	0.2 (***)	0.11 (***)	0.11 (***)	0.12 (***)											
ln(size)	−0.48 (***)	−0.35 (***)	−0.51 (***)	−0.55 (***)	−0.56 (***)	−0.08 (***)										
CDS slope	0.43 (***)	0.11	0.34 (***)	0.34 (***)	0.36 (***)	0.03 (***)	−0.4 (***)									
$IV_{1m} - HV_{12m}$	0.05	0.07 (*)	-0.25 (***)	0.22 (***)	0.04	0.02	−0.05	−0.01								
$IV_{1m} - IV_{12m}$	0.25 (***)	0.22 (***)	0.34 (***)	0.63 (***)	0.34 (***)	0.03 (**)	−0.25 (***)	0.11 (***)	0.54 (***)							
ln(CDS slope)	−0.32 (***)	−0.48 (***)	−0.23 (***)	−0.24 (***)	−0.25 (***)	−0.06 (***)	0.11 (**)	0.16 (***)	−0.03	−0.12 (***)						
$IV_{1m} - HV_{12m}$	0.04 (**)	0.04 (**)	−0.24 (***)	0.22 (***)	0.04	0.01	−0.07 (***)	0.01	0.88 (***)	0.52 (***)	−0.02 (*)					
$IV_{1m} - IV_{12m}$	0.2 (***)	0.16 (***)	0.31 (***)	0.56 (***)	0.29 (***)	0.02 (*)	−0.27 (***)	0.14 (***)	0.45 (***)	0.91 (***)	−0.08 (***)	0.53 (***)				
Straddle ret	−0.02 (***)	−0.02 (***)	−0.03 (***)	−0.01	−0.02 (***)	0	0.01 (**)	0	0.03 (***)	0.02 (***)	0.01 (**)	0.03 (***)	0.02 (***)			
Straddle ret (DH)	−0.02 (***)	−0.02 (***)	-0.03 (***)	−0.01	−0.02 (***)	0	0.01 (*)	0	0.04 (***)	0.02 (***)	0.01 (**)	0.04 (***)	0.03 (***)	0.96 (***)		
$\sigma_{IV_{1m}}$	0.45 (***)	0.41 (***)	0.54 (***)	0.63 (***)	0.56 (***)	0.09 (***)	−0.3 (***)	0.18 (***)	0.16 (***)	0.44 (***)	−0.18 (***)	0.12 (***)	0.37 (***)	0.00	0.00	

Note: Entries report the time-series average of the cross-sectional correlation matrix for selected variables. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately.

TABLE 3 | Regression on log CDS slope on other controlling factors.

	1	2	3	4	5	6	7	8	9
Constant	1.37 (***)	1.42 (***)	1.36 (***)	1.23 (***)	1.15 (***)	1.17 (***)	1.14 (***)	1.16 (***)	1.17 (***)
IV_{1m}	−0.71 (***)								
IV_{12m}		−0.89 (***)							
HV_{p12m}			−0.66 (***)						
$\sigma_{\mathrm{IV}_{1m}}$				−3.38 (***)					
$\mathrm{IV}_{1m} - \mathrm{IV}_{12m}$					−0.85 (***)			−0.83 (***)	
$\mathrm{IV}_{1m} - \mathrm{HV}_{12m}$						−0.30 (**)			−0.25 (**)
Jump							−1.32 (***)	−1.23 (***)	−1.19 (***)
R^2_{adj}	0.08	0.09	0.07	0.05	0.03	0.02	0.01	0.04	0.03

Note: At each date, we perform unconditional ordinary least square regressions on the cross-sectional log CDS Slope with different variables as explaining ones from regression 1 to regression 9. Entries report the sample averages of the coefficients and the adjusted R^2 for each regression. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance level of 1%, 5%, and 10% separately.

predicting power during normal periods. The empirical results are generally consistent with Table 4: the portfolio return increases with the increasing in log CDS slope; long-short trading strategy among all four option assets are positive and significant. Hence, at least, log CDS slope contains strong positive predictive power on future delta-hedged option return between 2002 and 2012, in either normal period or crisis period.

Table 6 reports trading performance of long-short strategy from 2013 to 2021, as the post period of Han Bing's sample. The reason is to test its predicting power in most recent years. Amazingly, the empirical results in Table 6 are contrary to those in Tables 4 and 5. The long-short strategy does not work in any of the four option assets: portfolio return seems to have no trend when increasing log CDS slope; the long-short trading strategy gets an insignificant revenue in all four option assets. We find selling option tend to lose money during this period, which is significantly different from the sample between 2002 and 2013. Hence, it raises us the motivation to explore how the trading performance works among the whole sample and whether the predictive power of log CDS slope varies with different market condition.

Table 7 reports trading performance of long-short strategy in full sample, from 2002 to 2021, with totally 20 years. The result looks like a weaker version of that of Table 4, as full sample contains the Han Bing's sample and post sample of Han Bing's. In summary, the portfolio return increases with increasing log CDS slope but with a lower upward trend; long-short trading strategy makes revenue in all four option assets, but with a smaller positive magnitude compared with those in Table 4.

Hence, based on the empirical results in Tables 4–7, we get known that, log CDS slope can strongly and positively predict cross-sectional delta-hedged option return before 2012, but it seems log CDS slope loss its sight after then. This motivates us to explore how the predictive power of log CDS slope on delta-hedged option return varies over time, even averagely it has a positive predictive power among the past 20 years.

5.3 | Risk Factor Premium on Option Return

Similar like exploring new risk factor in explaining stock return at cross-section, each new risk factor needs to show its significance after controlling traditional risk factors, generally within the Fama-Macbeth asset pricing regression. Hence, we perform the similar Fama-Macbeth regression on delta-hedged option return instead of stock return, and test the significance of log CDS slope after controlling traditional volatility mispricing factors.

Table 8 reports the Fama-Macbeth regression result, calculating the time-series average statistics on the cross-sectional regression of option return on risk factors, including log CDS slope, $\mathrm{IV}_{1m} - \mathrm{HV}_{12m}$, $\mathrm{IV}_{1m} - \mathrm{IV}_{12m}$, and $\sigma_{IV_{1m}}$. Before each cross-sectional regression, we normalize and winzorize the four factors within the range between −2 and 2. Panel A reports the results for straddle return, while the results for delta-hedged straddle return are shown in Panel B. The empirical results in Panel A and B are generally similar: log CDS slope can significantly predict future delta-hedged option return, but its

TABLE 4 | The long-short strategy on options in Han-Bing sample: 2002–2001 to 2012–2012.

	1	2	3	4	5	5-1
Panel A: Delta-hedged call return						
Return	0.91%	3.61%	4.57%	6.70% (**)	5.36%	4.45% (**)
Skew	−2.06	−2.79	−2.48	−2.88	−3.05	0.37
Kurt	8.48	12.99	9.49	13.08	13.86	2.32
Panel B: Delta-hedged put return						
Return	5.17% (*)	8.36% (***)	8.75% (***)	10.68% (***)	10.30% (***)	5.13% (**)
Skew	−2.36	−2.85	−3.44	−3.17	−3.25	0.33
Kurt	10.21	12.19	18.03	15.61	15.86	1.87
Panel C: Straddle return						
Return	2.57%	5.09% (**)	5.97% (**)	8.22% (***)	7.37% (**)	4.79% (**)
Skew	−2.06	−2.64	−2.42	−2.87	−3.25	0.41
Kurt	8.63	12.38	9.83	14.01	15.59	2.34
Panel D: Delta-hedged straddle return						
Return	3.11%	5.53% (**)	6.33% (**)	8.24% (***)	7.08% (**)	3.97% (**)
Skew	−2.23	−2.92	−2.57	−3.11	−3.21	0.46
Kurt	9.53	13.92	10.39	15.59	15.31	1.96

Note: Entries report time-series average monthly returns of portfolios sorted on the cross-sectional log CDS slope. The sample is selected fully following the criteria from Han et al. (2017), from 2002 January to 2012 December. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. The hedge ratio for the delta-hedged options are calculated using the current IV estimate. The options monthly returns are equal-weighted (for deciles), and the principle is the corresponding option price. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance level of 1%, 5%, and 10% separately.

TABLE 5 | The long-short strategy on options in Han-Bing sample exclude 2008–2009.

	1	2	3	4	5	5-1
Panel A: Delta-hedged call return						
Return	0.29%	2.70%	4.38%	5.36%	4.31%	4.02% (*)
Skew	−2.32	−3.06	−2.64	−2.97	−3.17	0.02
Kurt	10.33	14.77	10.82	14.04	14.73	1.56
Panel B: Delta-hedged put return						
Return	4.18%	8.01% (***)	8.46% (**)	10.09% (***)	10.04% (***)	5.86% (***)
Skew	−2.62	−2.94	−3.75	−3.33	−3.42	0.38
Kurt	11.82	13.5	20.82	17.54	17.61	0.46
Panel C: Straddle return						
Return	2.28%	4.39% (*)	5.64% (**)	7.34% (***)	6.69% (**)	4.41% (**)
Skew	−2.37	−2.92	−2.65	−2.99	−3.41	−0.09
Kurt	11.16	14.36	11.83	15.3	16.71	0.76
Panel D: Delta-hedged straddle return						
Return	2.43%	4.88% (*)	6.19% (**)	7.35% (**)	6.44% (**)	4.02% (**)
Skew	−2.53	−3.17	−2.72	−3.24	−3.36	0.17
Kurt	11.56	16.25	12.01	17.25	16.75	0.76

Note: Entries report time-series average monthly returns of portfolios sorted on the cross-sectional log CDS slope. The sample is selected fully following the criteria from Han et al. (2017), from 2002 January to 2012 December, while excluding the observations from 2008 January to 2009 December. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. The hedge ratio for the delta-hedged options are calculated using the current IV estimate. The options monthly returns are equal-weighted(for deciles), and the principle is the corresponding option price. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately,

TABLE 6 | The long-short strategy on options in post Han-Bing sample: 2013–2001 to 2021–2012.

	1	2	3	4	5	5-1
Panel A: Delta-hedged call return						
Return	−3.05%	−7.61%	−2.26%	−4.21%	−2.86%	0.19%
Skew	−8.37	−8.48	−8.42	−8.3	−8.01	0.69
Kurt	79.73	81.36	80.46	78.76	74.79	2.07
Panel B: Delta-hedged put return						
Return	0.75%	−1.08%	2.56%	−0.37%	0.49%	−0.25%
Skew	−8.73	−8.21	−8.53	−8.61	−8.19	1.79
Kurt	84.58	77.5	81.87	82.81	77.28	10.06
Panel C: Straddle return						
Return	−0.92%	−3.76%	0.16%	−2.02%	−0.76%	0.16%
Skew	−8.44	−8.54	−8.36	−8.18	−8.05	0.81
Kurt	80.83	82.19	79.78	77.15	75.41	3.01
Panel D: Delta-hedged straddle return						
Return	−0.63%	−3.35%	0.86%	−1.42%	−0.74%	−0.11%
Skew	−8.46	−8.33	−8.32	−8.32	−8.11	0.51
Kurt	80.98	79.25	79.03	78.93	76.2	1.48

Note: Entries report time-series average monthly returns of portfolios sorted on the cross-sectional log CDS slope. The sample is selected fully following the criteria from Han et al. (2017), from 2013 January to 2021 December. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. The hedge ratio for the delta-hedged options are calculated using the current IV estimate. The options monthly returns are equal-weighted(for deciles), and the principle is the corresponding option price. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance level of 1%, 5%, and 10% separately.

TABLE 7 | The long-short strategy on options in full sample: 2002–2001 to 2021–2012.

	1	2	3	4	5	5-1
Panel A: Delta-hedged call return						
Return	−0.96%	−1.55%	1.54%	1.81%	1.73%	2.69% (*)
Skew	−8.76	−9.78	−8.71	−8.47	−7.53	0.5
Kurt	106.19	124.66	104.19	99.12	81.26	2.05
Panel B: Delta-hedged put return						
Return	3.09%	4.07%	5.98% (*)	5.70%	5.96% (*)	2.87% (*)
Skew	−9.46	−9.02	−8.44	−9.28	−8.07	0.87
Kurt	118.43	109.55	96.5	113.64	90.78	4.13
Panel C: Straddle return						
Return	0.92%	1.08%	3.36%	3.61%	3.77%	2.85% (**)
Skew	−9.12	−10.04	−8.94	−8.65	−8	0.58
Kurt	113.02	129.88	109.03	102.85	89.58	2.5
Panel D: Delta-hedged straddle return						
Return	1.35%	1.51%	3.90%	3.89%	3.62%	2.27% (*)
Skew	−9.06	−9.56	−8.68	−8.79	−8.07	0.75
Kurt	111.44	120.15	103.55	104.72	90.87	1.72

Note: Entries report time-series average monthly returns of portfolios sorted on the cross-sectional log CDS slope. The sample is selected fully following the criteria from Han et al. (2017), from 2002 January to 2021 December. The returns on options are constructed using, as a reference beginning price, the average of the closing bid and ask quotes and, as the closing price, the terminal payoff of the option depending on the stock price and the strike price of the option. The hedge ratio for the delta-hedged options are calculated using the current IV estimate. The options monthly returns are equal-weighted (for deciles), and the principle is the corresponding option price. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance level of 1%, 5%, and 10% separately.

TABLE 8 | Unconditional option return analysis.

	1	2	3	4	5	6	7	8
Panel A: Straddle return								
Constant	0.0257	0.0269	0.0259	0.026	0.0271	0.0261	0.0262	0.0268
ln(CDS slope)	0.011 (**)				0.0128 (***)	0.0108 (**)	0.0102 (**)	0.0108 (***)
$IV_{1m} - IV_{12m}$		0.026 (***)			0.0273 (***)			0.0272 (***)
$IV_{1m} - HV_{12m}$			0.0369 (***)			0.0344 (***)		
$\sigma_{IV_{1m}}$				0.0079		0.0102		−0.0014
R^2_{adj}	0.0037	0.0079	0.0102	0.0076	0.0107	0.0128	0.0094	0.0144
Panel B: Delta-hedged straddle return								
Constant	0.0287	0.0301	0.029	0.0291	0.0302	0.0291	0.0293	0.03
ln(CDS slope)	0.0093 (* *)				0.0118 (***)	0.0096 (**)	0.0092 (**)	0.0099 (**)
$IV_{1m} - IV_{12m}$		0.0285 (***)			0.03 (***)			0.029 (***)
$IV_{1m} - HV_{12m}$			0.0385 (***)			0.0367 (***)		
$\sigma_{IV_{1m}}$				0.0089			0.0112	−0.0009
R^2_{adj}	0.0039	0.0077	0.0097	0.0076	0.0108	0.0126	0.0096	0.0144

Note: Entries report the time-series average of the cross-sectional regression of straddle return and delta-hedged straddle return. Panel A and B report the regression results for 1-month ATM straddle and delta-hedged ATM straddle separately. The controlling variables include IV_{1m} - HV_{12m} (Goyal and Saretto 2009),IV_{1m} - IV_{12m} (Vasquez 2017), and volatility of 1-month ATM implied volatility (σ_{IV1m}). The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance level of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

magnitude is smaller than traditional volatility risk factor measures. Focusing on Panel B, increasing 1 unit of log CDS slope can increase 0.94% monthly delta-hedged straddle return, but $IV_{1m} - HV_{12m}$ and $IV_{1m} - IV_{12m}$ can rise 3.85% and 2.86% separately. However, the one unit risk premium of log CDS slope does not be influenced by either $IV_{1m} - HV_{12m}$ or $IV_{1m} - IV_{12m}$ and remains stable around 0.95% when adding either one of them among the regression. This highlights log CDS slope contains different information apart from the traditional volatility mispricing factor to predict cross-sectional delta-hedged option return.

5.4 | Cumulative Option Return Over Whole Sample Horizon

After examining the predictive power of log CDS slope on delta-hedged option return in different sub-samples, exploring the determinants of log CDS slope, and analyzing the risk factor premium of log CDS slope on delta-hedged option return after controlling traditional volatility mispricing factors, the natural question becomes how the predictive power of log CDS slope on delta-hedged option return varies over time.

Figure 3 shows how the cumulative return of long-short trading strategy sorted by log CDS slope varies over time. Panel A and B among Figure 3 all reports the rolling average monthly return by applying long-short strategy on delta-hedged straddle, with only difference of rolling horizon.

Panel A of Figure 3, shows a consistently decreasing pattern for the average trading performance, by applying the cross-sectional long-short strategy on delta-hedged straddle sorting by log CDS slope. There exists some upward reversion during some crisis period, like 2008–2009 global financial crisis, 2012 European crisis, and 2020 Covid-crisis. But the general downward trend matches the efficient market hypothesis: there is no trading bible can beat the market forever.

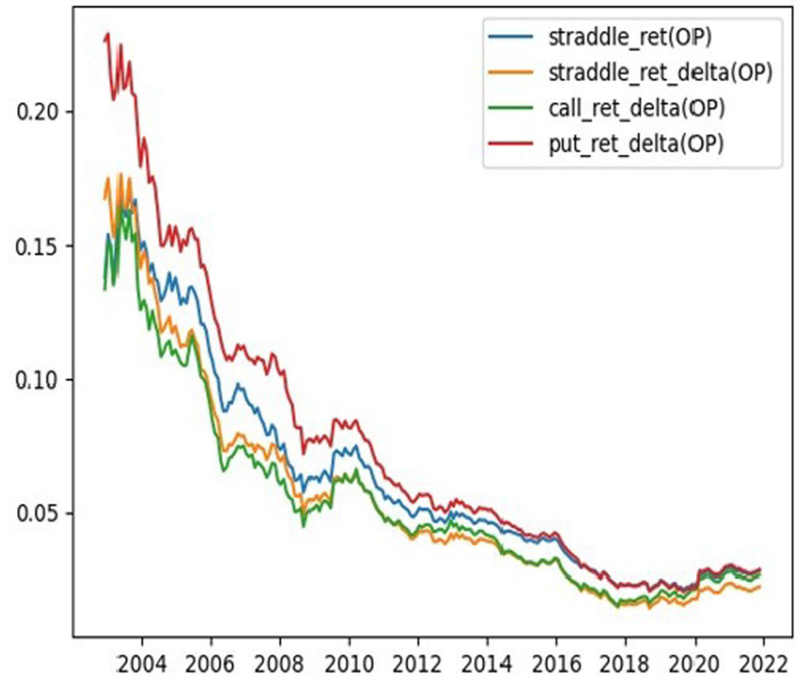
Panel B of Figure 3, shows 12-month rolling average monthly return, which exits a strong cycle pattern. Since 2008, the trading strategy get distinguish revenue in only two periods, between 2008 and 2009, and around 2020. Hence, the plot also points out, the predictive power of log CDS slope on delta-hedged option return may be conditional, especially when market is in volatile or crisis period.

6 | Conditional Empirical Test

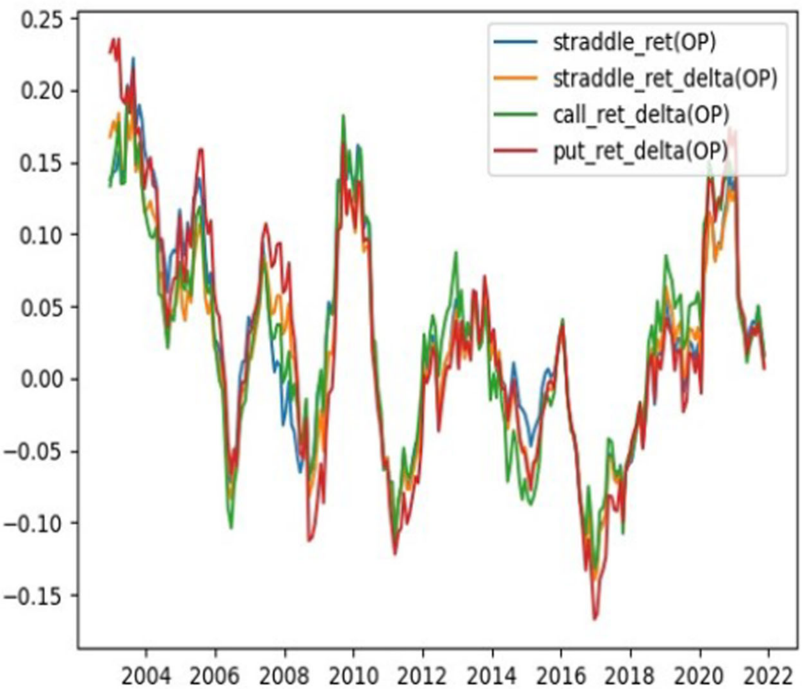
According to the results in unconditional empirical tests, we have enough confidence that, the predictive power of log CDS slope on delta-hedged option return is more like conditional rather than unconditional. Hence, in this section, we select several market condition proxies from market-level return and volatility perspectives to examine its time-varying predictive power. The market condition candidates include one return (past 1-year market return) and two volatilities (past 1-year market volatility and VIX). For each market condition candidate, we separate the sample into 5 sub-samples and examine how its predictive power varies over the 5 sub-samples.

6.1 | Market Condition Proxy: Market Return in Past 12 Months, R^M_{p12m}

To identify the market condition, the first natural choice is its first moment, market return over a specific horizon. In this



Panel A: Cumulative-Average Return



Panel B: Moving-Average 12-months Return

FIGURE 3 | Cumulative-average return and moving-average 12-months return. Figures show the time-series average return of long-short strategy on delta-hedged straddle. Panel A highlights the decreasing trend of this long-short trading strategy over the whole sample period. Panel B shows a cycle pattern of this long-short trading strategy within a 12-month rolling average framework. Panel A: Cumulative-average return. Panel B: Moving-average 12-months return. [Color figure can be viewed at wileyonlinelibrary.com]

sub-section, we use market return in past 12 months, R^M_{p12m}, where market return is constructed as the weighted average return for US firms listed in CRSP database with weights depending on most recent market capitalization.

Table 9 reports the quintile and long-short portfolio return for all four option investments across Panel A to Panel D over different rank of R^M_{p12m}. Among each each panel, columns represent five subperiod divided by market condition candidate:

TABLE 9 | Conditional long-short strategy on options: market return over past 12 months.

	1	2	3	4	5
Panel A: Delta-hedged call return					
1	−1.88%	−0.35%	8.5% (**)	−10.67%	−0.19%
2	1.65%	−1.34%	5.07%	−13.57%	0.58%
3	2.29%	3.80%	7.59% (**)	−9.51%	3.67%
4	7.27%	2.43%	6.98% (**)	−10.37%	8.04%
5	5.26%	2.62%	7.11% (**)	−8.72%	2.43%
5-1	7.14% (*)	2.98%	−1.40%	2.40%	2.23%
Panel B: Delta-hedged put return					
1	3.01%	4.63%	11.51% (***)	−7.50%	3.98%
2	4.10%	5.79%	11.14% (***)	−6.14%	5.62%
3	3.84%	9.04% (**)	13.14% (***)	−4.54%	8.57% (*)
4	5.55%	8.05% (**)	11.01% (***)	−6.74%	7.74%
5	9.21%	5.72%	12.62% (***)	−3.78%	6.16%
5-1	6.20%	1.09%	1.11%	3.72%	2.18%
Panel C: Straddle return					
1	−0.93%	2.80%	8.01% (**)	−7.99%	2.87%
2	2.08%	1.94%	7.68% (**)	−9.89%	3.74%
3	3.56%	5.94% (*)	7.84% (***)	−6.21%	5.77%
4	6.80%	5.26%	7.72% (**)	−7.45%	5.80%
5	6.35%	3.45%	9.49% (***)	−5.25%	4.94%
5-1	7.28% (*)	0.65%	1.48%	2.74%	2.07%
Panel D: Delta-hedged straddle return					
1	0.78%	2.17%	9.62% (***)	−7.93%	2.28%
2	3.07%	3.20%	7.62% (*)	−8.70%	3.41%
3	4.00%	6.18% (*)	9.38% (***)	−5.86%	5.97%
4	7.62%	5.25%	8.61% (***)	−7.25%	3.33%
5	6.69%	3.86%	9.10% (**)	−5.71%	4.90%
5-1	5.91%	1.70%	−0.53%	2.22%	2.01%

Note: Entries present the trading performance based on the market condition proxy: Market return over past 12 months. Panels A, B, C, and D represent the trading performance of delta-hedged call, delta-hedged put, straddle, and delta-hedged straddle separately. Among each panel, columns represent the five ranked periods determined by the market condition proxy, rows represent the five portfolios sorted by log CDS slope cross sectionally, and 5-1 means the long-short trading strategy. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

R^M_{p12m}. Each rank from 1 to 5 is obtained through comparing current market condition proxy value against full sample, where 1 means current market condition is within the lowest quintile bin compared with all historical values. Among each panel, rows represent quintile portfolios sorted by log CDS slope at cross-section, and 5–1 means the long-short strategy.

According to results in Panel A–D from Table 9, we have a common finding: the trading performance of long-short strategy is highest when market condition is at the lowest quintile bin (Rank (R^M_{p12m}) = 1). The average monthly return is 7.14%, 6.20%, 7.28%, and 5.91% for delta-hedged call, delta-hedged put, straddle and delta-hedged straddle separately, while these performances are much higher compared with other quintle bins of market condition proxy from 2 to 5. In summary, we find the predictive power of log CDS slope on delta-hedged option return is stronger when market return in past 1 year is at historical low level.

6.2 | Market Condition Proxy: Market Volatility in Past 12 Months, σ^M_{p12m}

To identify the market condition, rather than first moment of market return, we use historical volatility of market over a specific horizon, where second moment is always regarded as a risk measure. Moreover, academics find delta-hedged option return is related to volatility mispricing (Goyal and Saretto 2009). Hence market volatility in past 12 months, σ^M_{p12m} becomes a natural choice, where market index is weighted average of US firms listed in CRSP database.

Table 10 reports the quintile and long-short portfolio return for all four option investments across Panel A to Panel D over different rank of σ^M_{p12m}, which is same as Table 9. Comparing the results from Panel A to Panel D, four option investments share a same pattern. On the one hand, when σ^M_{p12m} is at a

TABLE 10 | Conditional long-short strategy on options: market volatility over past 12 months.

	1	2	3	4	5
Panel A: Delta-hedged call return					
1	0.97%	−9.98%	−7.88%	2.11%	9.85% (**)
2	2.54%	−16.96%	−9.99% (*)	1.04%	15.46% (***)
3	3.15%	−8.59%	−4.40%	−0.36%	17.78% (***)
4	1.72%	−12.84%	−5.08%	4.63%	20.46% (***)
5	1.15%	−8.56%	−6.28%	1.93%	20.24% (***)
5-1	0.18%	1.42%	1.60%	−0.18%	10.39% (***)
Panel B: Delta-hedged put return					
1	5.77% (*)	−7.87%	−3.26%	6.88%	13.81% (***)
2	8.79% (**)	−9.65%	−4.26%	4.86%	20.46% (***)
3	8.67% (**)	−3.07%	−0.17%	2.71%	21.79% (***)
4	7.37% (**)	−9.75%	−6.07%	7.70%	23.71% (***)
5	7.56% (**)	−3.29%	−4.40%	6.20%	23.49% (***)
5-1	1.79%	4.59%	−1.14%	−0.67%	9.68% (***)
Panel C: Straddle return					
1	3.68%	−8.66%	−4.43%	4.54%	9.37% (**)
2	4.63%	−12.19%	−5.89%	3.74%	14.97% (***)
3	4.66% (*)	−5.01%	−2.77%	2.56%	17.24% (***)
4	4.13%	−9.23%	−2.81%	6.26%	19.56% (***)
5	3.85%	−4.53%	−5.00%	4.70%	19.67% (***)
5-1	0.17%	4.12%	−0.57%	0.16%	10.3% (***)
Panel D: Delta-hedged straddle return					
1	3.67%	−8.04%	−4.92%	4.67%	11.25% (***)
2	4.97%	−11.67%	−6.10%	3.15%	16.76% (***)
3	5.18% (*)	−4.65%	−2.20%	2.33%	18.72% (***)
4	4.22%	−9.35%	−2.49%	6.33%	20.62% (***)
5	3.99%	−5.75%	−4.90%	4.27%	20.33% (***)
5-1	0.33%	3.29%	0.03%	0.40%	9.08% (***)

Note: Entries present the trading performance based on the market condition proxy: Market volatility over past 12 months. Panels A, B, C, and D represent the trading performance of delta-hedged call, delta-hedged put, straddle, and delta-hedged straddle separately. Among each panel, columns represent the five ranked periods determined by the market condition proxy, rows represent the five portfolios sorted by log CDS slope cross sectionally, and 5-1 means the long-short trading strategy. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

historical highest level ($\text{Rank}(\sigma^M_{p12m}) = 5$), selling delta-hedged option generally makes money compared with other ranks of σ^M_{p12m}. On the another hand, specifically, the cross-sectional predictive power of log CDS slope on delta-hedged option return only exits and becomes significant at 1% level when σ^M_{p12m} is at a historical highest level: quintile portfolio return gets higher with increasing log CDS slope. These findings generally matches those in Table 9: $\text{Rank}(R^M_{p12m}) = 1$ represents market performance is quite poor in past 1-year hence means a higher volatility in past 1-year, $\text{Rank}(\sigma^M_{p12m}) = 5$. But, σ^M_{p12m} seems to be a better market condition proxy compared with R^M_{p12m}: average monthly long-short return on four option investments is around 10% ($\text{Rank}(\sigma^M_{p12m}) = 5$), which is much larger than around 6.5% ($\text{Rank}(R^M_{p12m}) = 1$). In summary, we find the predictive power of log CDS slope on delta-hedged option return is stronger when market volatility in past 1 year is at historical high level.

6.3 | Market Condition Proxy: VIX

After using σ^M_{p12m} as market condition proxy, the natural market condition candidate becomes a Q-measure based volatility. Due to the Q-measure volatility calculated based on option data, VIX becomes the first choice as SPX option generally represent the market-level tradable option.

Table 11 reports the quintile and long-short portfolio return for all four option investments across Panel A to Panel D over different rank of VIX, which is same as Tables 9 and 10. The findings are general similar between Tables 11 and 10, for these two market condition candidates from volatility perspective. Across four option investments, long-short portfolio return becomes roughly average −4% (Rank(VIX) = 1) while that becomes averagely 6% (Rank(VIX) = 5). Wu and Xu (2022) finds a nonlinearity in mean reversion of volatility dynamics that,

TABLE 11 | Conditional long-short strategy on options: VIX.

	1	2	3	4	5
Panel A: Delta-hedged call return					
1	4.69%	−13.62%	−3.21%	−2.95%	10.26% (*)
2	−0.94%	−16.03%	−4.32%	0.76%	12.73% (**)
3	3.45%	−8.54%	−0.50%	−0.57%	13.82% (**)
4	0.88%	−13.25%	2.24%	4.16%	16.14% (***)
5	−0.45%	−9.58%	−3.15%	−0.95%	16.52% (***)
5-1	−5.14% (*)	4.03%	6.35% (**)	2.00%	6.27% (*)
Panel B: Delta-hedged put return					
1	9.46% (***)	−10.37%	2.72%	−0.20%	13.83% (***)
2	6.92% (*)	−8.17%	1.61%	5.97%	14.00% (**)
3	10.02% (***)	−3.80%	1.14%	3.67%	16.18% (***)
4	6.3% (*)	−8.17%	6.42% (*)	4.80%	19.15% (***)
5	6.16% (*)	−5.17%	5.8% (*)	3.53%	19.46% (***)
5-1	−3.30%	5.20%	3.08%	3.73%	5.63% (*)
Panel C: Straddle return					
1	5.81% (**)	−0.01%	0.06%	−1.31%	10.05% (*)
2	2.82%	−11.41%	−0.79%	2.19%	12.56% (***)
3	5.18% (**)	−4.98%	0.81%	2.19%	13.56% (***)
4	2.88%	−8.77%	0.44%	4.04%	15.82% (***)
5	2.62%	−6.15%	4.88%	1.72%	15.82% (***)
5-1	−3.20%	3.87%	4.82% (**)	3.03%	5.77%
Panel D: Delta-hedged straddle return					
1	6.7% (**)	−10.22%	−0.07%	−1.27%	11.58% (**)
2	3.02%	−10.84%	−0.92%	3.18%	13.07% (**)
3	6% (**)	−4.55%	1.29%	2.66%	15.09% (***)
4	3.58%	−9.26%	4.51%	4.33%	17.61% (***)
5	2.71%	−6.99%	4.12%	1.33%	16.97% (***)
5-1	−4.00%	3.24%	4.19% (*)	2.60%	5.39%

Note: Entries present the trading performance based on the market condition proxy: VIX. Panels A, B, C, and D represent the trading performance of delta-hedged call, delta-hedged put, straddle, and delta-hedged straddle separately. Among each panel, columns represent the five ranked periods determined by the market condition proxy, rows represent the five portfolios sorted by log CDS slope cross sectionally, and 5-1 means the long-short trading strategy. The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

volatility forecasting is much easier when historical volatility term structure is decreasing over time, and vice versa. Hence, both VIX and σ^M_{p12m} are just non-forecasting volatility proxies for future 1-month market volatility. Due to existence of variance risk premium, VIX is actually a biased expectation on future 1-month market-level volatility (Carr and Wu 2009). In summary, we find the predictive power of log CDS slope on delta-hedged option return is stronger when VIX is at historical high level, and the identification ability is at least as good as σ^M_{p12m}.

6.4 | Long-Short Strategy Performance Under Different Market Condition

In this sub-section, we show the time-series dynamics of rank for three market condition candidates and compare the performance of long-short strategy on delta-hedged straddle over five sub-periods determined by three market condition proxies.

Figure 4 show how rank orders of market condition candidates vary over time (Panel A–C) and long-short trading performance on delta-hedged straddle in each rank order for three market condition candidates (Panel D). Among Panel A–C, it reports the time-series rank orders for each market condition candidates separately. Among each of them, the values in *y*-axis are the rank orders of specific market condition proxy among full sample. In Panel D, we reports the portfolio return in each sub-sample sorted by different market condition proxies.

Panel A–C of Figure 4 indicate the strong time-varying patterns for different market conditions from return and volatility perspectives. R^M_{p12m} tends to move totally contrary to σ^M_{p12m} and

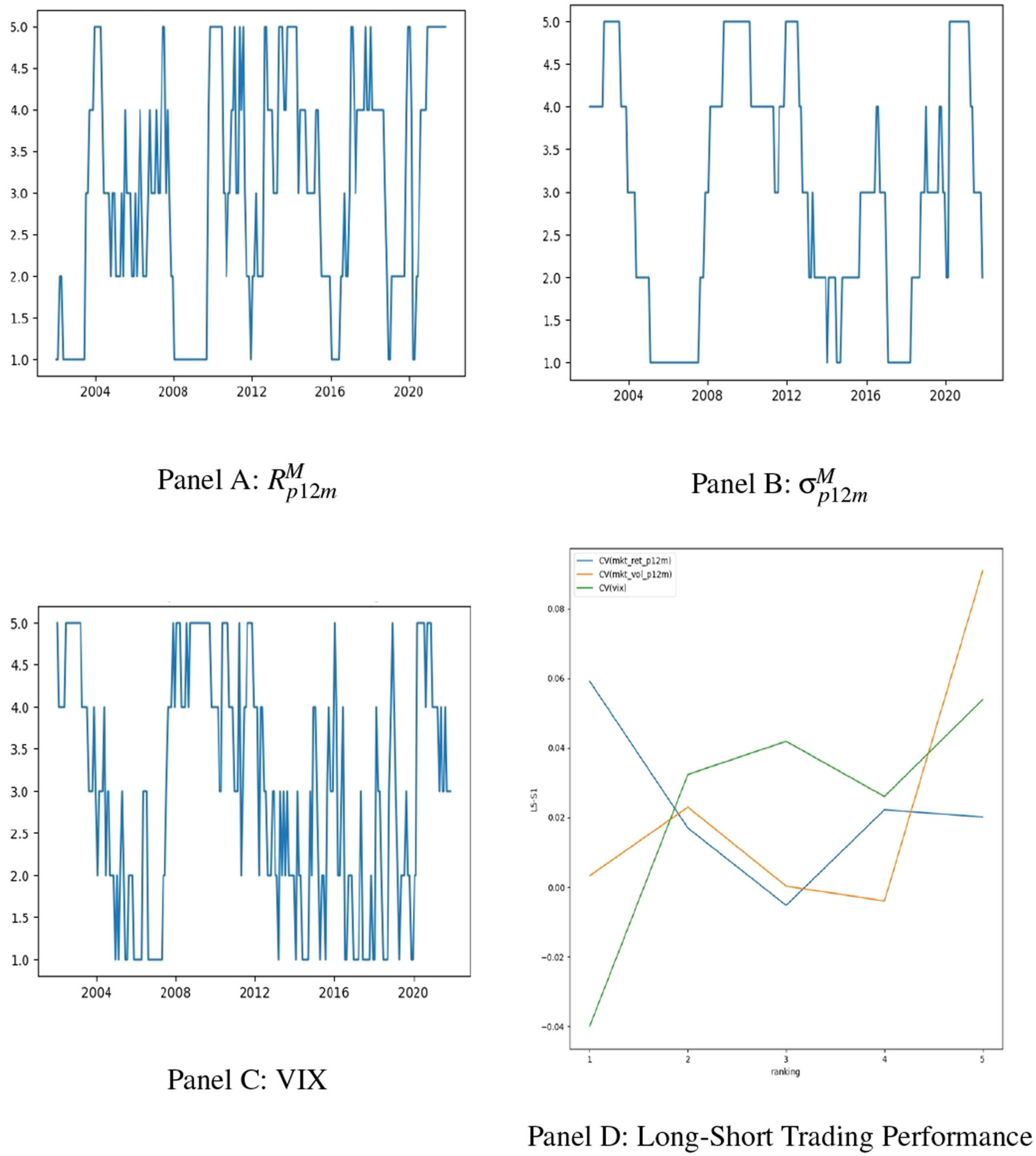


FIGURE 4 | Ranks of market condition proxies and long-short strategy on delta-hedged straddle. The plots show how rank orders of market condition proxies vary over time (Panel A, B, and C) and long-short trading performance in each rank order (Panel D). Among Panel A, B and C, each market condition proxy is ranked with values from 1 to 5 (y-axis values) in full sample. Among Panel D, the average monthly return of long-short strategy on delta-hedged straddle among five ranked sub-sample sorted by each market condition proxy is provided. Panel A: R^M_{p12m}. Panel B: σ^M_{p12m}. Panel C: VIX. Panel D: long-short trading performance. [Color figure can be viewed at wileyonlinelibrary.com]

VIX. For example during 2008–2009 financial crisis period, R^M_{p12m} stays at the lowest quintile, while σ^M_{p12m} and VIX quickly move to the highest quintile. Moreover, due to the different horizon choice, variation of VIX is much larger than that of σ^M_{p12m}, resulting in a quicker movement in its rank orders.

Panel D of Figure 4 shows the quintile portfolio return on delta-hedged straddle in five sub-periods sorted by three different market condition candidates separately. The result is consistent with Tables 9–11: quintile portfolio return increases with increasing rank order of σ^M_{p12m} and VIX while that decreases

TABLE 12 | Conditional straddle return analysis.

	1	2	3	4	5	6	7	8
Panel A: Rank 1 of VIX								
Constant	0.0391	0.0401	0.0394	0.0401	0.0406	0.0398	0.0405	0.0413
ln(CDS Slope)	−0.0088				−0.0084	−0.0073	−0.0061	−0.0068
$IV_{1m} - IV_{12m}$		0.0289 (**)			0.0295 (**)			0.0233 (*)
$IV_{1m} - HV_{12m}$			0.0449 (***)			0.0435 (***)		
$\sigma_{IV_{1m}}$				0.0249 (**)			0.0256 (**)	0.0184
R^2_{adj}	0.0008	0.0042	0.0057	0.0028	0.0049	0.0061	0.0036	0.0068
Panel B: Rank 2 of VIX								
Constant	−0.0827	−0.0799	−0.0814	−0.081	−0.0801	−0.0816	−0.0813	−0.0799
ln(CDS slope)	0.0132				0.0091	0.0105	0.0119	0.0087
$IV_{1m} - IV_{12m}$		0.0403			0.0402			0.0335
$IV_{1m} - HV_{12m}$			0.0457 (*)			0.0454 (*)		
$\sigma_{IV_{1m}}$				0.0323			0.0322	0.0188
R^2_{adj}	0.0009	0.0069	0.0091	0.0054	0.0075	0.0099	0.0061	0.0109
Panel C: Rank 3 of VIX								
Constant	0.0177	0.0186	0.0177	0.0191	0.0183	0.0175	0.0189	0.019
ln(CDS slope)	0.0146 (*)				0.0172 (**)	0.0149 (**)	0.016 (**)	0.0169 (**)
$IV_{1m} - IV_{12m}$		0.0233 (*)			0.0234 (*)			0.0204
$IV_{1m} - HV_{12m}$			0.035 (***)			0.0326 (***)		
$\sigma_{IV_{1m}}$				0.0175			0.0193	0.0119
R^2_{adj}	0.0014	0.008	0.011	0.005	0.0096	0.0118	0.0057	0.0126
Panel D: Rank 4 of VIX								
Constant	0.0159	0.0169	0.0162	0.0148	0.0171	0.0164	0.015	0.0158
ln(CDS slope)	0.0141				0.0195	0.0147	0.0088	0.0132
$IV_{1m} - IV_{12m}$		0.0271 (**)			0.0304 (**)			0.0428 (***)
$IV_{1m} - HV_{12m}$			0.029 (*)			0.0265 (*)		
$\sigma_{IV_{1m}}$				−0.0183			−0.0156	−0.0322
R^2_{adj}	0.0058	0.0063	0.0085	0.0085	0.0109	0.0132	0.0111	0.0176
Panel E: Rank 5 of VIX								
Constant	0.1382 (***)	0.1387 (***)	0.1375 (***)	0.137 (***)	0.1393 (***)	0.1381 (***)	0.1377 (***)	0.1379 (***)
ln(CDS slope)	0.0221 (*)				0.0267 (**)	0.0215 (*)	0.0207 (*)	0.0221 (**)
$IV_{1m} - IV_{12m}$		0.0102			0.013			0.0159
$IV_{1m} - HV_{12m}$			0.0298			0.024		
$\sigma_{IV_{1m}}$				−0.0165			−0.0105	−0.0235
R^2_{adj}	0.0097	0.0141	0.0164	0.0161	0.0205	0.0228	0.0205	0.0242

Note: Entries report the time-series average of the cross-sectional regression of straddle return. Panels A–E report the regression results for five sub-sample sorted by VIX. The controlling variables include $IV_{1m} - HV_{12m}$ (Goyal and Saretto 2009), $IV_{1m} - IV_{12m}$ (Vasquez 2017), and volatility of 1-month ATM implied volatility ($\sigma_{IV_{1m}}$). The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

TABLE 13 | Conditional delta-hedged straddle return analysis.

	1	2	3	4	5	6	7	8
Panel A: Rank 1 of VIX								
Constant	0.0445	0.0457	0.0448	0.0455	0.0462	0.0452	0.046	0.0469
ln(CDS slope)	−0.0113				−0.0106	−0.0098	−0.0088	−0.0093
$IV_{1m} - IV_{12m}$		0.0314 (***)			0.0318 (***)			0.0273 (**)
$IV_{1m} - HV_{12m}$			0.0455 (***)			0.044 (***)		
$\sigma_{IV_{1m}}$				0.0253 (**)			0.0257 (**)	0.0173
R^2_{adj}	0.0008	0.0041	0.0057	0.003	0.0048	0.0061	0.0038	0.007
Panel B: Rank 2 of VIX								
Constant	−0.0838	−0.0813	−0.0826	−0.0824	−0.0814	−0.0828	−0.0827	−0.0814
ln(CDS slope)	0.0115				0.0083	0.0095	0.0103	0.0078
$IV_{1m} - IV_{12m}$		0.0354			0.0354			0.0294
$IV_{1m} - HV_{12m}$			0.0446 (**)			0.0444 (**)		
$\sigma_{IV_{1m}}$				0.0263			0.0261	0.0144
R^2_{adj}	0.0016	0.0065	0.0093	0.0051	0.0078	0.0107	0.0065	0.0111
Panel C: Rank 3 of VIX								
Constant	0.0175	0.0186	0.0174	0.0189	0.0182	0.0172	0.0186	0.0188
ln(CDS slope)	0.0139 (*)				0.017 (**)	0.0142 (*)	0.0158 (**)	0.017 (**)
$IV_{1m} - IV_{12m}$		0.0275 (*)			0.0274 (*)			0.0258
$IV_{1m} - HV_{12m}$			0.0369 (***)			0.0348 (***)		
$\sigma_{IV_{1m}}$				0.0168			0.0183	0.0101
R^2_{adj}	0.0016	0.0095	0.0111	0.0046	0.0113	0.0122	0.0055	0.0141
Panel D: Rank 4 of VIX								
Constant	0.0179	0.0193	0.0182	0.0168	0.0194	0.0183	0.017	0.0179
ln(CDS slope)	0.0126				0.0182	0.013	0.0073	0.0116
$IV_{1m} - IV_{12m}$		0.0321 (***)			0.0361 (***)			0.0506 (***)
$IV_{1m} - HV_{12m}$			0.0311 (**)			0.0304 (**)		
$\sigma_{IV_{1m}}$				−0.0185			−0.0152	−0.0367 (*)
R^2_{adj}	0.0068	0.0064	0.008	0.0096	0.0118	0.0137	0.0126	0.0182

(Continues)

TABLE 13 | (Continued)

	1	2	3	4	5	6	7	8
Panel E: Rank 5 of VIX								
Constant	0.1471 (***)	0.148 (***)	0.147 (***)	0.1467 (***)	0.1486 (***)	0.1474 (***)	0.1474 (***)	0.1474 (***)
ln(CDS slope)	0.0201 (*)				0.0263 (**)	0.021 (**)	0.0215 (**)	0.0225 (**)
$IV_{1m} - IV_{12m}$		0.0158			0.0191			0.012
$IV_{1m} - HV_{12m}$			0.0341 (**)			0.0297 (**)		
$\sigma_{IV_{1m}}$				−0.0053			0.0011	−0.0092
R^2_{adj}	0.0089	0.0119	0.0145	0.0155	0.0182	0.0205	0.0194	0.0215

Note: Entries report the time-series average of the cross-sectional regression of delta-hedged straddle return. Panels A–E report the regression results for five sub-sample sorted by VIX. The controlling variables include $IV_{1m} - HV_{12m}$ (Goyal and Saretto 2009), $IV_{1m} - IV_{12m}$ (Vasquez 2017), and volatility of 1-month ATM implied volatility ($\sigma_{IV_{1m}}$). The Newey–West *t*-statistics in brackets are presented as ***, **, * with significance levels of 1%, 5%, and 10% separately. The sample period is from 2002 to 2021.

with increasing rank order of R^M_{p12m}. Especially, market condition candidate, VIX, tends to be a better sorting variable to determine the time-varying predicting power of log CDS slope.

6.5 | Analysis of Risk Factor Premium on Conditional Delta-Hedged Straddle Return

According to the findings in conditional long-short performance in Tables 9–11 and unconditional long-short performance in Table 7, it is natural to explore whether predicting power of log CDS slope can be explained by traditional volatility mispricing factors under different market conditions. VIX is selected as the market condition candidate in this sub-section, by considering its identification ability in previous sub-sections.

Table 12 shows how the risk premium of log CDS slope on monthly straddle return fluctuates across different market conditions: VIX, controlling the traditional volatility mispricing factors. Firstly, the average adjusted R^2 of straddle return explained by log CDS slope increases monotonously from 0.08% in Rank 1% to 0.97% in Rank 5; moreover, one unit impact of normalized log CDS slope factor, increases from −0.0088 (insignificant) in rank 1 to 0.0221 (significant at 10% level) in rank 5 and also changes the sign. Secondly, when looking at IV slope ($IV_{1m} - IV_{12m}$), its predictive power remains stable when rank of VIX increases from 1 to 4, but loses its significance at rank 5; moreover, one unit impact of normalized IV slope, decreases from 0.0289 (significant at 5% level) in Rank 1 to 0.0102 (insignificant) in rank 5. Thirdly, focusing on IV-HV slope ($IV_{1m} - HV_{12m}$), there exists a similar decreasing pattern like that in IV slope when increasing rank order of VIX; one unit impact of normalized IV-HV slope decreases from 0.0449 (significant at 1% level) in rank 1 to 0.0298 (insignificant) in rank 5. IV-HV slope tends to perform more persistent than IV slope when changing market condition, VIX. Fourthly, after controlling either two famous volatility mispricing factors or volatility of 1-month ATM IV, the predictive power of log CDS slope remain significant at either 5% and 10% level, when VIX is at rank 5. In summary, the predictive power of log CDS slope on straddle get stronger when VIX is higher.

Table 13 shows how the risk premium of log CDS slope on monthly delta-hedged straddle return fluctuates across different market conditions: VIX, controlling the traditional volatility mispricing factors. The main findings in Table 13 are nearly same as those in Table 12. These also match the findings from Pan (2002): when market volatility is high, jump risk premium dominates the risk premiums in 1-month ATM option contracts, compared with volatility risk premium. log CDS slope constructed as the difference between two CDS contracts, can be regarded as the difference between OTM put IV and its breakeven one and further excess jump risk premium, by using the URC theory proposed by Carr and Wu (2011). Hence, our finding, log CDS slope dominates the delta-hedged option return compared with traditional volatility mispricing factors when VIX is at historically high level, matches the literature finding in Pan (2002).

7 | Conclusion

The CDS spread reflects the intensity of default risk associated with the underlying company. The CDS slope, defined as the difference between CDS spreads of two different maturities, captures how default intensity evolves over time, representing the future credit risk trend. In this paper, we utilize the log CDS spread as a CDS-based volatility mispricing factor to predict delta-hedged straddle returns in the cross-section. Over the past two decades, we observe that the CDS slope varies significantly over time and across firms. More importantly, we find that the log CDS slope exhibits a strong and positive predictive ability for future 1-month delta-hedged straddle returns, particularly when market volatility is expected to be high.

We examine this forecasting relationship in two areas. The first is unconditional option return analysis. We examine its forecasting relationship in whole sample and confirm its significant and positive effect. We further use Fama-Macbeth regression to figure out whether its predictive power can be ruled out by other notable volatility mispricing factors, like $IV_{1m} - HV_{12m}$, or $IV_{1m} - IV_{12m}$. We confirm log CDS slope can predict delta-hedged straddle return strongly and, this positive relationship is not influenced by other volatility mispricing factors. Through examining this forecasting relationship among different samples, we find some clues for time-varying pattern.

Next, we investigate the forecasting relationship within a conditional analysis framework, focusing on how market conditions influence this relationship. We use three traditional market-level variables to segment the samples into sub-samples: past 1-year market return, past 1-year market volatility, and the VIX. Our findings reveal that the predictive ability of the log CDS slope varies significantly with market conditions. Specifically, it becomes more positive and pronounced when the past 1-year market return is at historically low levels, past 1-year market volatility is historically high, and the VIX is elevated. These empirical results highlight that the log CDS slope serves as a strong and positive predictor of future 1-month ATM delta-hedged straddle returns, particularly during periods of heightened market risk. This study bridges a gap in the literature by demonstrating how information from the CDS market spills over into the option market and contributes to conditional asset pricing, particularly within the option market.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

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