Empirical Analysis of Informed Trading Measures in the VIX Options Market

Chia-I Huang[1] Wei-Che Tsai[2] Hong-Gia Huang[3] Chia-Hsuan Lin[4]

1. Chia-I Huang (Corresponding Author) is a Ph.D. Candidate in the Department of Finance at National Sun Yat-sen University. Addr: No. 70 Lien-hai Road, Kaohsiung, Taiwan 804201. Tel: +886-7-525-2000, e-mail: crystal.hwg@gmail.com

2. Wei-Che Tsai is a Distinguished Professor of Finance at National Sun Yat-sen University and a Research Fellow at the Risk and Insurance Research Center at National Chengchi University. Addr: No. 70 Lien-hai Road, Kaohsiung, Taiwan 804201. Tel: +886-7-525-2000 Ext 4814, e-mail: weiche@mail.nsysu.edu.tw

3. Hong-Gia Huang is an Assistant Professor of Business Administration, Tunghai University. Addr: No. 1727, Sec. 4, Taiwan Boulevard, Xitun District, Taichung City, Taiwan 407224. Tel: +886-4-23590121 #35105, e-mail: honggiahuang@thu.edu.tw

4. Chia-Hsuan Lin obtained her master degree from Department of Finance at National Sun Yat-sen University. Addr: No. 70 Lien-hai Road, Kaohsiung, Taiwan 804201. Tel: +886-7-525-2000, e-mail: chiahsuan.lin.taiwan@gmail.com

Empirical Analysis of Informed Trading Measures in the VIX Options Market

Abstract

This study investigates the dynamics of high-frequency informed trading in the VIX options market, particularly examining the predictive capabilities of the implied volatility skew ($IVsk$), implied volatility spread ($IVsp$), and put-call ratio (PC). The analysis revealed that $IVsk$ and $IVsp$ both significantly predict VIX futures returns across various time intervals. This underscores their utility in capturing market dynamics, in contrast to the inconsistent predictive power of PC. Furthermore, the study explores the influence of market conditions, such as market uncertainty and liquidity, on these measures. It reveals that heightened uncertainty and reduced liquidity amplify the forecasting precision of $IVsk$. Additionally, the research highlights the significance of these measures during macroeconomic news releases and European market holidays, reflecting the nuanced interaction between global market participation and informed trading. Overall, the study emphasizes how $IVsk$ offers superior insight into informed trading for index volatility.

Keywords: informed trading; VIX options; implied volatility; implied volatility skew; implied volatility spread; put-call ratio

1. Introduction

Black and Scholes introduced the Black–Scholes model in 1973, which asserts that the market accurately prices options, thereby preventing market participants from gaining arbitrage profits through portfolios of options and corresponding stocks. This model, foundational to financial research, relies on specific assumptions that have been widely applied and scrutinized (Husmann & Todorova, 2011; Lehar, 2005). However, Easley et al. (1998) challenge the realism of these assumptions by demonstrating that informed traders exploit their knowledge to secure profits that are not necessarily confined to specific markets. They introduce the concept of "pooling equilibrium," which states that an informed trader's decision to operate within options or stock markets (or both) can influence the future pricing of underlying stocks, creating arbitrage opportunities. This equilibrium depends on the high-leverage options offered, the stock market's liquidity constraints, and the prevalence of informed traders. Further, the lower capital requirement for purchasing options (calls or puts) compared to directly trading stocks encourages investors to opt for options or a combination of stocks and options to maximize profits. Additionally, in scenarios where stock liquidity is insufficient, informed traders turn to options trading as a means to capitalize on their information advantage.

Subsequent research, such as Xing et al.'s (2010) study, supports this notion by demonstrating that informed traders actively participate in options markets, with the volatility smirk in options revealing fundamental information about the firm. Pan and Poteshman (2006) add to Easley et al.'s (1998) description of a pooling equilibrium by pointing out that options trading volumes can predict the future prices of the underlying stocks, attributing this predictive capability to informed trading activities rather than market inefficiencies. They emphasize the significant roles played by the concentration of informed traders and the leverage provided by options contracts.

Moreover, studies have established that derivatives can forecast the underlying asset's price, attributed to information traders' preference for these financial instruments (Hu, 2014; Lee et al., 2021). Chordia et al. (2021) explored this dynamic by examining information trading through order flow analysis in index options. They found empirical evidence that demonstrates a significant relationship between net put buying and the weekly returns of the S&P 500 Index. These studies underscore the intricate dynamics between informed trading, market mechanisms, and the predictive power of futures and options, highlighting the evolving understanding of how information dissemination impacts financial markets.

In high-frequency trading (HFT), the rapid dissemination of information facilitates informed traders' concealment of private information. Consequently, this complicates the analysis of the relationship between trading activities and the transmission of price-related information. HFT has caused the fragmentation of asset trading across diverse markets, including stocks, futures, and options. This fragmentation has resulted in increased trading speeds, which has had a significant impact on market liquidity and the price discovery process. HFT enhances market efficiency by mitigating pricing inefficiencies and facilitating trades that predict future price movements despite potentially introducing adverse selection costs to other market participants (Brogaard et al., 2014).

Given the VIX index's position as a barometer for short-term market volatility predictions, options provide a unique opportunity to investigate the relationship between HFT and informed trading. Since its introduction in 1993, the VIX, often called the "investor fear gauge," has become the benchmark for gauging stock market volatility (Zhang & Zhu, 2006). In 1973, the establishment of the Chicago Board Options Exchange (CBOE) heralded the advent of the first centralized options trading market in the United States. This development resulted in significant growth and established a prominent position in the financial sector. The increasing need to hedge against volatility risk has propelled VIX options to prominence, marking them as some of the CBOE's most acclaimed products. According to CBOE Global Markets, Inc., the average daily trading volume for VIX options increased to 492,000 contracts in 2020, up from 132,000 contracts in 2009, representing a nearly 3.73-fold increase. This surge underscores the extensive market engagement with VIX options, which are characterized by their significant liquidity and trading volume. These attributes render these options an apt subject for in-depth investigations into informed trading, particularly within an HFT environment. The foundational research by Easley et al. (1998) has spurred a wealth of studies, consistently demonstrating that informed traders leverage options markets to maximize profits and minimize trading costs. This backdrop provides the VIX with substantial liquidity and trading volume, which makes it an ideal subject for this study.

The VIX index measures the anticipated volatility of the S&P 500 Index over the next 30 days, reflecting option investors' perceptions of future market volatility. Higher index values signal anticipated increased volatility, whereas lower values indicate expectations of diminished volatility. The indirect tradability of the VIX, through its options, offers investors mechanisms to speculate on or hedge against anticipated market movements. By analyzing the predictive ability of certain option-related metrics in the VIX options market, this study aims to investigate the presence of informed trading within the VIX options market. Specifically, it focuses on the implied volatility skew ($IVsk$), implied volatility spread ($IVsp$), and put-call ratio (PC) as predictors of intraday returns on VIX futures. The research explores the nuances of traditional HFT dynamics, distinguishing them from the rapid, large-scale algorithmic strategies that are often associated with this domain. It also enhances our understanding of how these metrics may signal informed trading activities and their impact on market movements in the context of VIX futures.

Our findings demonstrate that $IVsk$ of VIX options accurately predicts the returns on VIX futures within subsequent 15-minute intervals, with $IVsp$ also providing valuable, predictive insights. Further, our analysis confirms the sustained predictive accuracy of $IVsk$ and

$IVsp$ over 15-, 30-, and 45-minute intervals. In contrast, PC does not show significant predictive value for future interval returns. These findings substantiate the existence of informed trading activities within the VIX options market and align with the studies of Xing et al. (2010) and Chan et al. (2015), which suggest that $IVsk$ and $IVsp$ effectively capture the information content inherent in options trading activities.

Further analysis explores the impact of various factors, including market volatility (economic policy uncertainty and realized volatility) and market liquidity (Amihud (2002) illiquidity and trading volume), on these predictive relationships. Our empirical evidence suggests that the predictability of $IVsk$ becomes more pronounced under conditions of heightened market uncertainty and diminished liquidity. However, we observe no distinct trends for the other two metrics under varying market conditions. These findings support Kyle's (1985) hypothesis and Chordia et al.'s (2021) observation that the value of information escalates during periods of increased market uncertainty. This is due to increase of non-informational traders' trading volume in uncertain markets, thereby creating additional opportunities for traders who have private information. Furthermore, our results corroborate the arguments of Chordia et al. (2008) and Ferreira et al. (2017) that the price impact of informed trading becomes more pronounced during low-liquidity periods, thereby reflecting a decrease in market efficiency.

Further, our analysis reveals that $IVsk$ successfully identifies volatility-informed trading around the time of macroeconomic announcements. This indicates that VIX options can be a viable tool for informed traders seeking to leverage macroeconomic information. Such findings align with the studies conducted by Bernile et al. (2016), which demonstrate the visibility of informed trading activities in proximity to macroeconomic news releases.

Finally, our findings demonstrate that $IVsk$ is a significant predictor of VIX futures returns on trading days following European holidays. However, the predictive strength significantly decreases on days when the European stock market remains closed. This pattern underscores that European investors' participation markedly enhances the demand for VIX futures , thereby increasing volatility-informed trading activities within the VIX options market. Our conclusive empirical evidence supports the previous research by Bondarenko and Muravyev (2023) and Huang et al. (2023), which emphasize the crucial role of European investors in the VIX futures market.

Overall, this study contributes to a broader understanding of the dynamics of informed trading within the VIX options and futures market. It highlights the nuanced roles of specific option-related metrics under various market conditions. Crucially, our investigation reveals that $IVsk$ encompasses more information regarding volatility trading activities within the VIX options market compared to the other metrics analyzed. This observation indicates that informed traders prefer using out-of-the-money (OTM) put contracts as their primary method for leveraging volatility information. The rationale behind this preference lies in the unique ability of $IVsk$ to encapsulate information through the disparity in implied volatility between OTM put contracts and at-the-money (ATM) call contracts. Such a differential potentially corroborates the findings presented by Xing et al. (2010) and Chordia et al. (2021), which indicate a predominance of informed trading activities within index put options over call options[1]. Moreover, it supports the argument of Chakravarty et al. (2004) and Pan and Poteshman (2006) that greater predictability and more informed trading exist in options contracts with greater leverage.

The culmination of this research on the dynamics of informed trading within the VIX options market offers several pivotal contributions to academic literature and practical market understanding. By dissecting the predictive power of option-related metrics—such as, $IVsk$, $IVsp$, and PC—this study provides a nuanced exploration of how these variables can signal

[1] In other words, investors exhibit a preference for OTM puts as a strategy to hedge against anticipated future negative price movements. This behavioral trend results in an increase in the demand for OTM puts, consequently elevating their price and, by extension, the implied volatility prior to significant market downturns.

informed trading activities and their subsequent impact on VIX futures intraday returns. This investigation's meticulous differentiation between traditional HFT dynamics and the more rapid, algorithmic strategies, often conflated within this context, stands out.

Our findings strongly support the concept that informed trading has a significant impact on the VIX futures market, as seen by $IVsk$ and $IVsp$'s predictive abilities across several time intervals. This not only substantiates the theoretical frameworks posited by seminal works in financial research, but also expands on them by demonstrating these metrics' practical applicability in forecasting market movements. These insights are particularly valuable in an era where the rapid dissemination of information through HFT mechanisms complicates the landscape of market liquidity and price discovery.

In sum, this study contributes significantly to financial research in various ways. First, it illuminates the intricate dynamics of informed trading within the VIX options market. Second, it elucidates the predictive value of specific option-related metrics. Third, it provides empirical evidence that enhances our understanding of market behavior under varying conditions. These contributions bridge theoretical gaps in the literature and offer practical insights for market participants, policymakers, and regulators, who are seeking to navigate or oversee the ever-evolving landscape of financial markets. Using a thorough analytical framework, this study emphasizes the importance of informed trading in determining market dynamics and the nuanced impact of HFT on financial market efficiency and predictability.

The rest of this paper is structured as follows: Section 2 presents the data and methodology used. Section 3 details the data utilized for empirical analysis. Section 4 discusses the results of the extended analysis. Section 5 provides concluding remarks, encapsulating the study's contributions to understanding the intricate dynamics between VIX options, futures, and HFT.

2. Data and Methodology

2.1 Data

In this study, we used a CBOE dataset containing high-frequency transaction data related to VIX futures and options. The dataset covers an extensive period from January 2008 to December 2015, totaling 2023 trading days. To maintain the integrity and applicability of our analysis, we restricted our examination to transactions conducted during the standard trading hours, which began at 8:30 a.m. till 3:15 p.m. Additionally, to ensure a focus on market segments with sufficient liquidity to analyze informed trading activities, we limited our dataset to contracts with maturity periods ranging between 10 and 60 days. We rigorously filtered the dataset to eliminate any entries containing missing data or identifiable data errors. Finally, as part of our data preparation process, we employed the algorithm by Lee and Ready (1991) to classify the directional execution of trades, thereby enhancing our analytical approach's precision and academic rigor.

2.2 Variable Definition

2.2.1 Implied Volatility Skew

The implied volatility skew ($IVsk$) of VIX options is recognized as a critical metric for identifying informed trading activities. In options trading, the term "volatility smile" refers to a pattern in which plotting implied volatility versus changing strike prices for options with the same expiry and underlying asset produces a smile-like curve. This indicates disparities in implied volatilities across different strike prices, typically demonstrating elevated implied volatility at or near the ATM strike price, culminating in a smile-shaped curve. Contrary to the idealized symmetry of a volatility smile, markets more frequently exhibit a "volatility smirk." Conversely, investors demonstrate a marked preference (compared with ATM calls) for OTM puts as a hedging mechanism against expected future declines in asset prices. This behavioral pattern results in an increased demand for OTM puts, which subsequently drives up their prices and, consequently, increases the implied volatility before notable market corrections. Therefore, IV skew manifests as a disparity in implied volatilities between OTM puts and ATM calls.

Extensive research, including studies by Beer and Fink (2019), Jia et al. (2021), and Nappo et al. (2023), thoroughly examine the implications of the IV skew, commonly known as the volatility smirk and its correlation with future asset returns. Specifically, Xing et al. (2010) investigate the link between the volatility smirk and subsequent returns of the underlying stocks. They discover a significant association between the IV skew and future cross-sectional equity returns. This implies that informed traders may exploit options market efficiencies and leverage before stock prices fully adjust.

To explore the predictive power of IV skews on asset returns, particularly in intraday trading, we incorporate $IVsk$ as a variable in this study. We define the IV skew for a given time interval, t, denoted as $IVsk_t$, through the following formula:

$$IVsk_{i,t} = \frac{1}{N_t}\sum_{j=1}^{N_{i,t}}(IV_{j,t}^{OTMPut} - IV_{j,t}^{ATMCall}) \quad (1)$$

where $IVsk_t$ is the IV skew for an interval of time t. Additionally, j expresses the pairing of ATM call options and OTM put options with the same expiry and strike price. N_t represents the aggregate quantity of call options that are ATM and put options that are OTM, forming pairs within time interval t. $IV_{j,t}^{OTMPut}$ is the IV skew of an OTM put option that is matched to an ATM call option with the same strike price and expiration date within the t-th time interval. $IV_{j,t}^{ATMCall}$ is the IV skew of an ATM call option that is matched to an OTM put option with the same strike price and expiration date within the t-th time interval.

2.2.2 Implied Volatility Spread

Derived from the pricing of options on underlying assets, the concept of implied volatility encapsulates the market's consensus on the future volatility of those assets. Investors critically value this measure for its utility in leveraging positions, hedging risks, and disseminating private information. Consequently, the predictive power of implied volatility regarding asset returns is a focal point of scholarly investigation.

$IVsp$ in VIX options, which is defined as the differential between the implied volatilities of call and put options, indicates the private information that informed investors may possess regarding the future price movements of the underlying asset. In contrast to previous research, Doran et al. (2013) introduce a novel perspective by identifying a negative association between $IVsp$ and the subsequent returns of OTM call options. This observation implies that $IVsp$ integrates insights not only on the underlying assets' fundamentals but also on discrepancies in option pricing. Atilgan (2014) supports the premise that $IVsp$ is predictive of returns following major announcements, indicating the presence of informed trading.

In our research, we employ the method delineated by Chan et al. (2015) for calculating $IVsp$, focusing on options with identical strike prices and expiration dates. We compute $IVsp$ by averaging the implied volatility differences between calls and puts for each specified time horizon using the following mathematical representation:

$$IVsp_t = \frac{1}{N_t}\sum_{j=1}^{N_t}(IV_{j,t}^{Calls} - IV_{j,t}^{Puts}) \tag{2}$$

where $IVsp_t$ represents $IVsp$ with the specific *t*-th time interval[2]. $IV_{j,t}^{Calls}$ and $IV_{j,t}^{Puts}$ denote the implied volatility of VIX call and put options with the same contract condition j (identical strike prices and expiry dates) in the *t*-th interval.

2.2.3. Put-call Ratios

Trading volume is a critical indicator of market information, particularly in the asset-derivative market. Prior research has extensively explored the dynamics between the trading volume of options and the pricing of underlying assets or other derivatives, underscoring the informational value of trade volumes (Cao et al., 2005; Easley et al., 1998). Pan and Poteshman

---

[2] Although existing literature predominantly examines the correlation between implied volatility spread and returns over daily, weekly, or monthly periods, our research diverges by exploring the predictive capability of the implied volatility spread on the returns from intraday trading activities. This approach aims to discern the efficacy of the implied volatility spread as an indicator for short-term market movements and trader sentiment within the condensed timeframe of a trading day.

(2006) examine the predictive relationship between the options trading volume (specifically PC derived from new positions initiated by purchasers) and stock prices. Their findings underscore the efficacy of the options volume in conveying significant market information. Furthering this inquiry, Zhou (2022) scrutinizes the interplay between options and stock markets, specifically focusing on the informative impact of the options trading volume relative to moneyness and maturity. The study reveals a negative correlation between the ratio of options volume to stock volume and stock returns, highlighting the pivotal role of information in this context.

Given the established significance of PC as a conduit of market information, this study explores the relationship between PC of VIX options and the intraday returns of VIX futures. Drawing upon the Pan and Poteshman's (2006) method, PC in this investigation is quantified as:

$$PC_t = \frac{Put_t}{Call_t + Put_t} \tag{3}$$

For a given interval *t*, $Call_t$ and Put_t are the trading volumes of call and put contracts, respectively, initiated by buyers.

2.3 Regression Settings

To explore the presence of informed traders operating at high frequency within the VIX options market and their influence on the volatility market, our study assesses the predictive power of specific variables—namely, the implied volatility skew ($IVsk$), the implied volatility spread ($IVsp$), and the put-call ratio (PC)—on the returns of VIX futures over 15-minute intervals. Therefore, we implement the following regression model:

$$VIXRET_t = \alpha_0 + \beta_1 IVsk_{t-1} + \beta_2 IVsp_{t-1} + \beta_3 PC_{t-1} + \sum_{i=1}^{4} \beta_4 VIXRET_{t-i} + \sum_{i=1}^{4} \beta_5 \Delta FTV_{t-i} + \sum_{i=1}^{4} \beta_6 FILLIQ_{t-i} + \varepsilon_{i,t} \tag{4}$$

where $VIXRET_t$ refers to the VIX futures returns and is defined as the logarithmic difference between the closing and opening prices for a given futures contract within the time interval *t*.

$IVsk_t$ refers to the implied volatility skew, $IVsp_t$ denotes the implied volatility spread, and PC_t represents the put-call ratio. ΔFTV_{t-i} is the change in VIX futures trading volume within the time interval t and $FILLIQ_{t-i}$ refers to the VIX futures' Amihud (2002) illiquidity measure within the time interval t, which is defined as the absolute VIX futures returns divided by the VIX futures trading volume ($\times 10^4$ in adjusting the coefficient) in the time interval *t*.

2.4 Summary Statistic

Table 1 provides a comprehensive overview of the descriptive statistics for VIX options, utilizing data gathered from January 1, 2008, to December 31, 2015. It is organized into three panels: Panel A aggregates the total volume of call and put options traded in the market, whereas Panels B and C specifically detail the statistics for call options and put options, respectively. The analysis reveals that the average 15-minute trading volume for VIX call options surpasses that of VIX put options. This discrepancy indicates a predominant investor preference for utilizing call options to speculate on future market volatility. However, the extent to which these trading behaviors contain anticipatory information regarding future volatility requires further exploration in the following sections of this work.

------Insert Table 1 here------

Table 2 presents summary statistics for various critical variables, including returns on VIX futures ($VIXRET$), $IVsk$, $IVsp$, and PC, as detailed in Panel A. The data indicates an average return of approximately 1.9% on VIX futures. Furthermore, the mean values for the $IVsk$, $IVsp$, and PC are computed as 0.631, 1.119, and 0.348, respectively.

Panel B displays a correlation matrix featuring $VIXRET$, $IVsk$, $IVsp$, PC, ΔFTV (the change in futures trading volume), and $FILLIQ$ (the Amihud illiquidity measure of VIX futures). Among these variables, the correlation coefficients do not exceed 0.7, indicating no significant concerns regarding multicollinearity. VIX futures returns exhibit substantial relationships with $IVsk$, $IVsp$, and PC in negative, positive, and negative directions, respectively. This analysis provides preliminary evidence that supports our theoretical framework.

------Insert Table 2 here------

3. Empirical Results

3.1 Informed Trading in the VIX Options Market

Table 3 presents the regression outcomes for the primary measures of informed trading—$IVsk$, $IVsp$, and PC—across distinct regression frameworks. Subsequently, Table 4 consolidates these informed trading metrics within a single regression model to scrutinize their predictive accuracy for returns.

As exhibited in Table 3, the regression results reveal a negative relationship between $IVsk_{t-1}$ and the subsequent 15-minute returns on VIX futures across columns (1) to (4), resembling the findings of Xing et al. (2010). This suggests a pronounced inclination among informed traders towards OTM put contracts as a strategic instrument for capitalizing on volatility information. The implied volatility skew's ability to aggregate information, as highlighted by the differential in implied volatilities between OTM put contracts and ATM call contracts, evidences this preference. Conversely, the coefficients for $IVsp_{t-1}$ are significantly positive across columns (5) to (8), implying a positive association between $IVsp_{t-1}$ and the returns on VIX futures in the ensuing 15-minute period ($VIXRET_t$). This observation aligns with Chan et al.'s (2015) research, which posits that $IVsp$ adeptly encapsulates the information content pertinent to options trading dynamics.

Our analysis does not support the hypothesis that PC (PC_{t-1}) is a significant predictor of the subsequent 15-minute returns on VIX futures. This finding suggests that the ratio of trading volume between long put and call options does not effectively capture informed trading activities within the VIX options market. A plausible explanation for this observation is that informed traders do not solely rely on purchasing VIX options to leverage their private information. Instead, they may employ various strategies, including combinations of long puts and short calls, to hedge against expected future declines in market prices. This simple approach to trading based on single pieces of information may dilute the predictive power of PC as a measure of informed trading behavior.

------Insert Table 3 here------

Our comprehensive analysis integrates the informed trading metrics into a unified regression model to evaluate their predictive efficacy for returns on VIX futures, as detailed in Table 4. The outcomes, mirroring the insights from Table 3, reveal that the coefficients for $IVsk_{t-1}$ and $IVsp_{t-1}$ exhibit negative and positive associations with the subsequent 15-minute returns on VIX futures, respectively. Conversely, Table 4 reaffirms the lack of significant predictive capability for PC, thereby underscoring the premise that a simplistic model of trading predicated on singular informational cues may compromise $PC's$ effectiveness as an indicator of informed trading conduct.

Overall, our empirical findings not only corroborate earlier studies by demonstrating that $IVsk$ and $IVsp$ proficiently encapsulate the information content of trading activities but also substantiate the presence of high-frequency informed trading within the VIX options market. This underscores the strategic deployment of volatility information by traders in this domain.

------Insert Table 4 here------

3.2 Informed Trading in the VIX Options Market Across Different Levels of Market Uncertainty

In this section, this study examines the predictive power of three key informed trading metrics—$IVsk$, $IVsp$, and PC—across varying market conditions, focusing on market volatility or uncertainty. Drawing on Kyle (1985), we indicate that within standard informed trading models, the informational value escalates amidst increased market uncertainty. Chordia et al. (2021) observe that less sophisticated traders are more likely to engage in options market activities under heightened volatility, a scenario that provides informed traders with opportunities to capitalize on their private information. Additionally, Chordia et al. (2019) identify a surge in informed trading activity preceding events that amplify information asymmetry. Ferreira et al. (2017) also highlight the prevalence of asymmetric information during periods marked by economic instability.

Based on these insights, we hypothesize that periods of significant market uncertainty enhance the predictive accuracy of our informed trading indicators. We anticipate that $IVsk_{t-1}$, $IVsp_{t-1}$, and PC_{t-1} will demonstrate increased significance when assessed against measures of high market uncertainty. To test this hypothesis, we employ two proxies for market uncertainty—economic policy uncertainty (EPU)[3] and realized volatility[4]—as benchmarks. Subsequently, we apply Equation (4) to different levels of market uncertainty to better understand the relationship between varying degrees of market uncertainty and the predictive efficacy of informed trading metrics in forecasting returns.

Table 5 shows that $IVsk_{t-1}$ is significantly negative in periods of high EPU, observed consistently across varying levels of uncertainty (90%, 80%, 70%, or 67%) within our sample. Conversely, no substantial evidence implies that $IVsk_{t-1}$ predicts returns negatively when EPU is deemed low (10%, 20%, 30%, or 33%). Additionally, the analysis indicates that $IVsp_{t-1}$ and PC_{t-1} are insignificant, demonstrating a relatively weaker predictive strength for returns in the VIX options market when compared to $IVsk_{t-1}$.

[3] Baker et al. (2016) developed a comprehensive index to quantify policy-related economic uncertainty, incorporating three distinct components. Newspaper coverage serves as the primary component, where a systematic approach quantifies the frequency of articles discussing policy-related economic uncertainty. In addition to the newspaper-based metric, the index also incorporates data concerning the volatility of federal tax code provisions and the diversity of economic forecasts. The final component of the index utilizes the dispersion in forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

[4] We compute the realized volatility as the standard deviation of all of the 15-minute VIX futures returns in a given day.

Furthermore, as detailed in Table 6, the predictive capacity of $IVsk_{t-1}$ remains significantly negative during high volatility periods, irrespective of the market volatility being 90%, 80%, 75%, or 67% high (and insignificantly so when volatility is 10%, 20%, 25%, or 33% low) within the sample. However, the study does not find significant evidence that $IVsp_{t-1}$ and PC_{t-1} are effective during times of heightened market volatility.

Cumulatively, our empirical findings corroborate the assertions made by Kyle (1985), Chordia et al. (2021), and Ferreira et al. (2017) regarding the amplification of informational value and informed trading activities amidst increased market uncertainty. Moreover, they illustrate the superior predictive capability of implied volatility skew over other informed trading measures in the VIX options market. This implies that $IVsk$ captures a broader spectrum of information relevant to volatility trading activities within the VIX options market compared to the alternative metrics analyzed.

------Insert Table 5 here------

------Insert Table 6 here------

3.3 Informed Trading in the VIX Options across Different Levels of Market Liquidity

Beyond examining market uncertainty, our analysis explores how market liquidity influences the predictive efficacy of informed trading indicators. Chordia et al. (2008) suggest that the return predictability associated with informed trading metrics, such as order imbalance, diminishes in contexts of heightened market liquidity due to the market's increased capacity to absorb order flows. Conversely, Ferreira et al. (2017) highlight a positive correlation between market illiquidity and information asymmetry. They observe that informed domestic institutions tend to increase their trading activity during periods characterized by low liquidity. Considering this hypothesis, we adopt two liquidity metrics for our examination: the Amihud (2002) illiquidity measure and the overall trading volume. Specifically, the Amihud illiquidity measure quantifies market liquidity by calculating the ratio of absolute daily returns on VIX futures to the total dollar trading volume in the VIX futures market, with a higher value signifying reduced liquidity. Utilizing these liquidity indicators, we apply Equation (4) to various levels of Amihud illiquidity and trading volume to assess the relationship between market liquidity and the informed trading measures' capacity to forecast returns.

Table 7 reveals that $IVsk_{t-1}$ exhibits a significant negative relationship with subsequent VIX futures returns when the Amihud (2002) illiquidity measure is at heightened levels (90%, 80%, 75%, or 67%) within our sample. In contrast, compelling evidence to assert that $IVsk_{t-1}$ adversely predicts returns under conditions of low Amihud (2002) illiquidity (10%, 20%, 25%, or 33%) is lacking. Additionally, the results indicate a positive and significant association between $IVsp_{t-1}$ and subsequent VIX futures returns during periods when the Amihud (2002) measure is 75% and 67% elevated. Conversely, PC_{t-1} does not demonstrate a significant impact on returns across varying levels of market liquidity.

Further, Table 8 elaborates on the predictive strength of $IVsk_{t-1}$ during periods characterized by low trading volumes, showcasing their significance regardless of trading volume levels being low (10%, 20%, 25%, or 33%)—a trend that diminishes as trading volume intensifies (90%, 80%, 75%, or 67%). However, this analysis does not yield significant evidence to substantiate the influence of PC_{t-1} in scenarios of either elevated or diminished market liquidity. These findings not only underscore the nuanced roles of $IVsk_{t-1}$ in predicting VIX futures returns but also highlight the limited predictive utility of PC_{t-1} across different liquidity conditions.

The findings suggest that informed traders exhibit a strong preference for operating in conditions of market illiquidity. This inclination enhances the effectiveness of $IVsk$ and $IVsp$ in capturing relevant information, particularly as market liquidity reduces. This observation aligns with and reinforces the conclusions of Chordia et al. (2008) and Ferreira et al. (2017), who argue that the effects on prices stemming from informed trading intensify in scenarios of reduced market liquidity.

------Insert Table 7 here------

------Insert Table 8 here------

3.4 Informed Trading in the VIX Options around the Macroeconomic Announcement

This section explores whether informed traders exploit VIX options to capitalize on macroeconomic news. We examine the efficacy of informed trading metrics around specific macroeconomic disclosures, such as the Consumer Price Index (CPI), Gross Domestic Product (GDP), and Federal Open Market Committee (FOMC) meetings. By applying Equation (4) around the announcement periods,[5] we aim to discern the correlation between macroeconomic news and informed trading measures, thereby assessing their ability to forecast returns.

The results, as detailed in Table 9, demonstrate a meaningful influence of $IVsk_{t-1}$ and $IVsp_{t-1}$ on subsequent returns around the macroeconomic news release dates. These empirical results support the findings of Bernile et al. (2016), which demonstrate the detectability of informed trading activities in proximity to macroeconomic announcements and indicate that VIX options may serve as an instrument for informed traders seeking to leverage macroeconomic information.

------Insert Table 9 here------

3.5 European Investors and Informed Trading Activities of the VIX Options

Bondarenko and Muravyev (2023) observe a pattern where the VIX futures experience an increase during overnight sessions, followed by a pronounced decline with the opening of European markets. This observation implies that European investors play a significant role in assimilating overnight information through their active participation in the VIX futures market, thereby diminishing prevailing uncertainty. Similarly, Chen et al. (2021) identify that the VIX

[5] We extracted a subsample from two days before the announcement date to two days after the announcement date during the sample period of January 1, 2008, to December 31, 2015.

futures demonstrate notable overnight returns, especially on Mondays or days succeeding holidays, underscoring the role of trading activities in mitigating uncertainty as markets resume. In addition, Huang et al. (2023) demonstrate that trading on the European market increases the demand for volatility derivatives, which leads to stronger intraday momentum in the VIX futures.

These findings underscore the integral role of the VIX market, particularly in its correlation with international markets such as the European stock market, in serving as a vital hedging avenue for international investors against volatility. Considering these observations, our research aims to explore two pertinent inquiries: (1) Does the resumption of the European stock market catalyze increased informed trading within the VIX options market? (2) Is there a diminution in informed trading within the VIX options market attributable to the closure of the European stock market for holidays? Given the concurrent trading hours between the European and US markets, the holiday effect in Europe warrants a focused investigation. The potential lack of European investors, who are informed about volatility, from the VIX options market during the holidays can significantly influence the market's information content.

To address the posed questions, our methodology categorizes trading days into two distinct groups: the holiday group, comprising days when the VIX options market operates while the European market observes a holiday, and the non-holiday group, encompassing the trading days in the VIX options market after the European market reopens. Subsequently, we conduct regression analyses separately for each group.

Table 10 reveals that $IVsk_{t-1}$ significantly predicts VIX futures returns at the 1% significance level on the trading days after the European holidays. In contrast, the predictive strength of $IVsk_{t-1}$ diminishes markedly on days when the European stock market is closed for holidays. The findings illustrated in Table 10 indicate that European investors' participation in the market significantly amplifies demand for VIX futures, resulting in an increase in volatility-informed trading activities within the VIX options market. Concisely, our empirical results support the findings of Bondarenko and Muravyev (2023) and Huang et al. (2023) that European investors, through their active involvement in the VIX futures market, play a vital role in enhancing informational efficiency, thereby effectively mitigating prevailing uncertainty.

3.6 Robustness Checks

Our analysis re-evaluates $IVsk$, $IVsp$, and PC over varied time intervals (specifically 30 and 45 minutes) to ascertain the efficacy of informed trading metrics.

Table 10 presents our findings, indicating that $IVsk_{t-1}$ and $IVsp_{t-1}$ exhibit significant negative and positive correlations, respectively, with the returns on the VIX futures in the subsequent 30 and 45-minute intervals. Conversely, PC_{t-1} shows no significant effect on the VIX futures returns in the same time frames.

Our comprehensive study confirms that $IVsk$ and $IVsp$ are reliable predictors of the future VIX returns at 15-, 30-, and 45-minute intervals. This observation underscores the continued relevance of $IVsk$ and $IVsp$ as informative measures, whereas PC does not exhibit a consistent predictive capability for returns in subsequent intervals. These outcomes empirically support the concept of informed trading within the VIX options market, resonating with the insights provided by Xing et al. (2010) and Chan et al. (2015). These scholars posit that $IVsk$ and $IVsp$ aptly encapsulate the informational content prevalent in options trading dynamics.

------Insert Table 10 here------

4. Conclusions

This study explores the dynamics of high-frequency informed trading within the VIX options and futures market, specifically focusing on the predictive capabilities of well-known option-related measures such as $IVsk$, $IVsp$, and PC. We observed that both implied volatility skew and implied volatility spread provide valuable predictive insights into the returns on VIX futures across different time intervals, namely 15, 30, and 45 minutes. This finding aligns with prior literature, such as the studies of Xing et al. (2010) and Chan et al. (2015), which highlights the information-capturing prowess of these measures. Conversely, the PC measure did not exhibit a consistent predictive capability, suggesting that it has limited usefulness in capturing informed trading behavior in the context of VIX derivatives.

Our exploration extends to analyzing the impact of market conditions, specifically EPU and market liquidity, on the efficacy of informed trading metrics. Our findings reveal a complex environment where increased market uncertainty and diminished liquidity amplify the predictive accuracy of the $IVsk$. Empirical evidence from Chordia et al. (2021) supports this enhancement in predictive power, illustrating the intricate nature of informed trading that thrives in contexts marked by elevated uncertainty and pronounced information asymmetry.

Furthermore, our analysis indicates a distinct preference among informed traders for navigating through periods of low market liquidity. This strategy significantly enhances the utility of both $IVsk$ and $IVsp$ in identifying critical information as liquidity constraints tighten. This trend corroborates the findings of Chordia et al. (2008) and Ferreira et al. (2017), who contend that the price impacts attributed to informed trading are more pronounced in conditions of decreased market liquidity.

Further, our research reveals the significant impact of $IVsk$ and $IVsp$ on subsequent returns, particularly around macroeconomic news release dates. This finding underscores the potential of VIX derivatives as crucial instruments for informed traders aiming to capitalize on macroeconomic information. These empirical results support the findings of Bernile et al. (2016), which demonstrate the detectability of informed trading activities in proximity to macroeconomic announcements.

We explore the European holiday effect to bolster our argument regarding volatility-informed trading. Due to the overlapping trading sessions between the US and European markets, holidays in Europe present a unique opportunity to observe variations in trading dynamics. Specifically, we hypothesize that the lack of European informed investors during their market holidays would diminish the informed trading activities in the VIX options market, thereby reducing the return predictability of informed trading metrics. Our analysis confirms this hypothesis, revealing a significant decline in the predictive strength of $IVsk$ on European holidays. Conversely, $IVsk$ significantly predicts the VIX future returns on trading days following European holidays. This implies that European investor participation escalates the trading demand for volatility derivatives and enhances volatility-informed trading in the VIX options market. Our empirical evidence corroborates the observations of Bondarenko and Muravyev (2023) and Huang et al. (2023), which demonstrate that European investors, through their active participation in the VIX futures market, significantly contribute to improving informational efficiency and, consequently, effectively reducing existing market uncertainty.

Overall, our study demonstrates that $IVsk$ provides a comprehensive insight into volatility trading dynamics within the VIX options market, surpassing other metrics. This finding reflects a discernible inclination among informed traders towards utilizing OTM put contracts to exploit volatility information. The preference arises from the distinct capability of $IVsk$ to capture critical information via the volatility discrepancy between OTM put contracts and ATM call contracts. This disparity aligns with the observations of Xing et al. (2010) and Chordia et al. (2021), which highlight a dominance of informed trading in index put options compared to call options. Moreover, it reinforces the argument made by Chakravarty et al. (2004) and Pan and Poteshman (2006) regarding the enhanced predictability and prevalence of informed trading in higher-leverage options contracts.

This study contributes to the current corpus of financial research by providing empirical evidence on the nuanced functions of key option-related indicators under different market conditions in the VIX futures market. Notably, our findings enhance the comprehension of how informed trading activities utilize option market dynamics to forecast future market moves. Furthermore, this study sheds light on the differential predictive capabilities of various informed trading measures, providing valuable insights into their relevance and applicability in real-world trading and investment strategies.

For future research directions, this study provides opportunities for further exploration. One potential area involves further exploring the mechanisms through which informed traders utilize VIX options in anticipation of macroeconomic announcements, while also considering the regulatory frameworks that govern information dissemination. Additionally, future studies can explore the interplay between informed trading activities and other derivative instruments, extending the analysis to a broader array of financial markets and instruments. Another intriguing path may entail machine learning and advanced statistical approaches to enhance the predictive models that capture informed trading behavior. This could lead to the discovery of more nuanced insights into informed traders' strategic decisions.

In conclusion, our study enhances the understanding of informed trading dynamics in the VIX options market, highlighting the critical role of option-related metrics in predicting market movements. Therefore, this research enriches academic discourse and provides practical implications for market participants seeking to navigate the complexities of financial markets.

ACKNOWLEDGEMENT

We thank the National Science and Technology Council of Taiwan for supporting us. The contributions of Hsin-Yu Chiu (National Central University), Te-Feng Chen (The Hong Kong Polytechnic University), Chi-Lu Peng (National Kaohsiung University of Science and

Technology), Yaw-Huei Jeffrey Wang (UNSW Business School), John Wei (The Hong Kong Polytechnic University), and Jimmy Yang (Oregon State University) have also greatly influenced our work.

References

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6

Atilgan, Y. (2014). Volatility spreads and earnings announcement returns. *Journal of Banking & Finance*, *38*, 205–215. https://doi.org/10.1016/j.jbankfin.2013.10.007

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Beer, S., & Fink, H. (2019). Dynamics of foreign exchange implied volatility and implied correlation surfaces. *Quantitative Finance*, *19*(8), 1293–1320. https://doi.org/10.1080/14697688.2019.1575517

Bernile, G., Hu, J., & Tang, Y. (2016). Can information be locked up? Informed trading ahead of macro-news announcements. *Journal of Financial Economics*, *121*(3), 496–520. https://doi.org/10.1016/j.jfineco.2015.09.012

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654. https://doi.org/10.1086/260062

Bondarenko, O., & Muravyev, D. (2023). Market return around the clock: A puzzle. *Journal of Financial and Quantitative Analysis*, *58*(3), 939–967.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *The Review of Financial Studies*, *27*(8), 2267–2306. https://doi.org/10.1093/rfs/hhu032

Cao, C., Chen, Z., & Griffin, J. M. (2005). Informational content of option volume prior to takeovers. *The Journal of Business*, *78*(3), 1073–1109. https://doi.org/10.1086/429654

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and Option markets. *The Journal of Finance*, *59*(3), 1235–1257. https://doi.org/10.1111/j.1540-6261.2004.00661.x

Chan, K., Ge, L., & Lin, T.-C. (2015). Informational content of options trading on acquirer announcement return. *Journal of Financial and Quantitative Analysis*, *50*(5), 1057–1082. https://doi.org/10.1017/S0022109015000484

Chen, J., Jiang, G. J., Yuan, C., & Zhu, D. (2021). Breaking VIX at open: Evidence of uncertainty creation and resolution. *Journal of Banking & Finance*, *124*, 106060.

https://doi.org/10.1016/j.jbankfin.2021.106060

Chern, K.-Y., Tandon, K., Yu, S., & Webb, G. (2008). The information content of stock split announcements: Do options matter? *Journal of Banking & Finance*, *32*(6), 930–946. https://doi.org/10.1016/j.jbankfin.2007.07.008

Chordia, T., Hu, J., Subrahmanyam, A., & Tong, Q. (2019). Order flow volatility and equity costs of capital. *Management Science*, *65*(4), 1520–1551. https://doi.org/10.1287/mnsc.2017.2848

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, *87*(2), 249–268. https://doi.org/10.1016/j.jfineco.2007.03.005

Chordia, T., Kurov, A., Muravyev, D., & Subrahmanyam, A. (2021). Index option trading activity and market returns. *Management Science*, *67*(3), 1758–1778. https://doi.org/10.1287/mnsc.2019.3529

Doran, J. S., Fodor, A., & Jiang, D. (2013). Call-put implied volatility spreads and option returns. *Review of Asset Pricing Studies*, *3*(2), 258–290. https://doi.org/10.1093/rapstu/rat006

Easley, D., O'Hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *The Journal of Finance*, *53*(2), 431–465. https://doi.org/10.1111/0022-1082.194060

Ferreira, M. A., Matos, P., Pereira, J. P., & Pires, P. (2017). Do locals know better? A comparison of the performance of local and foreign institutional investors. *Journal of Banking & Finance*, *82*, 151–164. https://doi.org/10.1016/j.jbankfin.2017.06.002

Fleming, M. J., & Remolona, E. M. (1999). Price formation and liquidity in the US Treasury market: The response to public information. *The Journal of Finance*, *54*(5), 1901–1915.

Hu, J. (2014). Does option trading convey stock price information? *Journal of Financial Economics*, *111*(3), 625–645. https://doi.org/10.1016/j.jfineco.2013.12.004

Husmann, S., & Todorova, N. (2011). CAPM option pricing. *Finance Research Letters*, *8*(4), 213–219. https://doi.org/10.1016/j.frl.2011.03.001

Huang, H. G., Tsai, W. C., Weng, P. S., & Yang, J. J. (2023). Intraday momentum in the VIX futures market. *Journal of Banking & Finance*, *148*, 106746. https://doi.org/10.1016/j.jbankfin.2022.106746

Jia, X., Ruan, X., & Zhang, J. E. (2021). The implied volatility smirk of commodity options. *Journal of Futures Markets*, *41*(1), 72–104. https://doi.org/10.1002/fut.22161

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315–1335. https://doi.org/10.2307/1913210

Kyle, A. S., & Vila, J. L. (1991). Noise trading and takeovers. *The RAND Journal of Economics*, 54–71. https://doi.org/10.2307/2601007

Lee, J., Ryu, D., & Yang, H. (2021). Does vega-neutral options trading contain infor mation? *Journal of Empirical Finance*, *62*, 294–314. https://doi.org/10.1016/j.jem pfin.2021.04.003

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*(10), 2577–2603. https://doi.org/10.1016/j.jbankfin.2004.09.007

Lee, C. M., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733–746. https://doi.org/10.1111/j.1540-6261.1991.tb02683.x

Nappo, G., Marchetti, F. M., & Vagnani, G. (2023). Traders' heterogeneous beliefs ab out stock volatility and the implied volatility skew in financial options markets. *Finance Research Letters*, *53*, 103664. https://doi.org/10.1016/j.frl.2023.103664

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787. https://doi.org/10.2307/2526578

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future sto ck prices. *The Review of Financial Studies*, *19*(3), 871–908. https://doi.org/10.10 93/rfs/hhj024

Xing, Y., Zhang, X., & Zhao, R. (2010). What does the individual option volatility smirk tell us about future equity returns? *Journal of Financial and Quantitative Analysis*, *45*(3), 641–662. https://doi.org/10.1017/S0022109010000220

Zhang, J. E., & Zhu, Y. (2006). VIX futures. *Journal of Futures Markets*, *26*(6), 521–531. https://doi.org/10.1002/fut.20209

Zhou, Y. (2022). Option trading volume by moneyness, firm fundamentals, and expected stock returns. *Journal of Financial Markets*, *58*, 100648. https://doi.org/10.1016/j.fin-mar.2021.100648

Table 1. Descriptive statistics of the VIX option.

Panel A: Option market (Call and Put)						
	Mean	S.D.	Median	Max	Min	Observations
Trading Volume	118.0	259.0	68.3	23,922	1.0	58,158
Strike Price	24.7	8.92	22.40	91.40	10.00	58,158
Trading Price	1.81	1.14	1.54	39.60	0.05	58,158
Days to Maturity	31.1	6.7	31.9	57.0	11.7	58,158
Panel B: Call option market						
	Mean	S.D.	Median	Max	Min	Observations
Trading Volume	112.0	295.0	57.9	31,428	1.0	58,051
Strike Price	26.30	10.20	23.80	95.90	10.00	58,051
Trading Price	1.77	1.24	1.47	39.60	0.05	58,051
Days to Maturity	31.3	6.8	32.1	58.0	11.0	58,051
Panel C: Put option market						
	Mean	S.D.	Median	Max	Min	Observations
Trading Volume	115.0	289.0	52.0	20,000.0	1.0	56,839
Strike Price	20.9	7.34	18.9	85	10.00	56,839
Trading Price	1.96	1.79	1.54	45.2	0.01	56,839
Days to Maturity	30.6	7.88	31.1	58.00	11.00	56,839

Panels A, B, and C report summary statistics of trading volume, strike price, trading price, and days to maturity in the total option, call option, and put option markets, respectively. The sample period ranged from January 1, 2008, to December 31, 2015.

Table 2. Summary statistics of the VIX futures return, IV skew, IV spread, and put-call ratio.

Panel A: Descriptive statistics						
	Mean	S.D.	Median	Max	Min	N
VIXRET	0.019	0.047	0.0028	0.370	-0.400	54,640
IVsk	0.613	0.036	0.625	0.655	0.522	28,278
IVsp	1.119	0.018	1.113	1.160	1.090	49,898
PC	0.348	0.307	0.2612	1.000	0.000	49,533

Panel B: Correlations						
	VIXRET	*IVsk*	*IVsp*	*PC*	*ΔFTV*	*FILLIQ*
VIXRET	1					
IVsk	-0.205***	1				
IVsp	0.223***	-0.657***	1			
PC	-0.010**	-0.017***	-0.003	1		
ΔFTV	0.003	0.004	-0.030***	0.005	1	
FILLIQ	-0.046***	-0.051***	0.049***	0.007	-0.006	1

Panel A presents summary statistics of VIX futures return (VIXRET), IV skew (IVsk), IV spread (IVsp), and the put-call ratio (PC) for the sample period from January 1, 2008, to December 31, 2015. Panel B reports the correlations between VIXRET, IVsk, IVsp, PC, the change of future trading volume (ΔFTV), and Amihud (2002)'s illiquidity measure for VIX futures (FILLIQ), while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Predictive capability of returns of implied volatility skew, implied volatility spread, and the put-call ratio.

Dep.								$VIXRET_t$						
	(1)	*(2)*	*(3)*	*(4)*		*(5)*	*(6)*	*(7)*	*(8)*		*(9)*	*(10)*	*(11)*	*(12)*
C	0.050***	0.007***	0.007***	0.007***	C	-0.030***	-0.005***	-0.005***	-0.006***	C	0.023***	0.002***	0.002***	0.002***
	(66.127)	(10.897)	(10.587)	(10.632)		(-33.436)	(-7.536)	(-7.495)	(-7.497)		(55.540)	(5.436)	(5.290)	(5.438)
$IVsk_{t-1}$	-0.046***	-0.007***	-0.007***	-0.007***	$IVsp_{t-1}$	0.048***	0.008***	0.008***	0.008***	PC_{t-1}	-0.000	0.000	0.000	0.000
	(-41.514)	(-8.158)	(-7.982)	(-8.420)		(59.323)	(11.850)	(11.732)	(11.754)		(-0.211)	(0.548)	(0.647)	(0.677)
$VIXRET_{t-1}$		0.253***	0.254***	0.258***	$VIXRET_{t-1}$		0.231***	0.232***	0.232***	$VIXRET_{t-1}$		0.244***	0.246***	0.245***
		(13.283)	(13.043)	(13.640)			(13.432)	(13.159)	(13.234)			(13.858)	(13.385)	(13.429)
$VIXRET_{t-2}$		0.208***	0.206***	0.205***	$VIXRET_{t-2}$		0.192***	0.193***	0.192***	$VIXRET_{t-2}$		0.205***	0.202***	0.202***
		(11.525)	(11.250)	(11.195)			(11.668)	(11.467)	(11.482)			(11.593)	(11.136)	(11.133)
$VIXRET_{t-3}$		0.206***	0.208***	0.208***	$VIXRET_{t-3}$		0.216***	0.214***	0.215***	$VIXRET_{t-3}$		0.225***	0.225***	0.225***
		(11.187)	(11.014)	(10.930)			(12.868)	(12.515)	(12.574)			(13.165)	(12.589)	(12.612)
$VIXRET_{t-4}$		0.236***	0.234***	0.232***	$VIXRET_{t-4}$		0.232***	0.231***	0.231***	$VIXRET_{t-4}$		0.233***	0.234***	0.235***
		(11.852)	(11.540)	(11.447)			(13.078)	(12.734)	(12.817)			(12.077)	(11.757)	(11.853)
ΔFTV_{t-1}			-0.000	-0.000	ΔFTV_{t-1}			0.000	0.000	ΔFTV_{t-1}			-0.000	-0.000
			(-0.729)	(-0.857)				(0.083)	(0.044)				(-0.487)	(-0.487)
ΔFTV_{t-2}			-0.000***	-0.000***	ΔFTV_{t-2}			-0.000**	-0.000**	ΔFTV_{t-2}			-0.000**	-0.000**
			(-3.292)	(-3.318)				(-2.044)	(-1.992)				(-2.313)	(-2.234)
ΔFTV_{t-3}			-0.000**	-0.000*	ΔFTV_{t-3}			-0.000	-0.000	ΔFTV_{t-3}			-0.000	-0.000
			(-2.007)	(-1.960)				(-1.108)	(-1.173)				(-1.544)	(-1.556)
ΔFTV_{t-4}			-0.000	-0.000	ΔFTV_{t-4}			-0.000	-0.000	ΔFTV_{t-4}			-0.000	-0.000
			(-0.248)	(-0.159)				(-0.634)	(-0.673)				(-0.759)	(-0.736)
$FILLIQ_{t-1}$				-0.000*	$FILLIQ_{t-1}$				-0.000	$FILLIQ_{t-1}$				-0.000
				(-1.656)					(-0.137)					(-0.212)
$FILLIQ_{t-2}$				0.000	$FILLIQ_{t-2}$				0.000	$FILLIQ_{t-2}$				0.000
				(0.379)					(1.388)					(0.820)
$FILLIQ_{t-3}$				0.000	$FILLIQ_{t-3}$				-0.000	$FILLIQ_{t-3}$				-0.000
				(0.444)					(-1.406)					(-1.350)
$FILLIQ_{t-4}$				0.000	$FILLIQ_{t-4}$				0.000	$FILLIQ_{t-4}$				0.000
				(0.279)					(0.565)					(0.484)
R^2	0.124	0.711	0.706	0.707	R^2	0.120	0.631	0.627	0.627	R^2	0.000	0.639	0.636	0.636
N	25,216	22,893	21,874	21,874	N	43,426	26,880	25,586	25,586	N	43,177	26,895	25,379	25,376

This table delineates the effects of implied volatility skew, implied volatility spread, and the put-call ratio on the returns of VIX futures throughout the sample period spanning January 1, 2008, to December 31, 2015. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Return predictability of implied volatility skew, implied volatility spread, and the put-call ratio.

Dep.	$VIXRET_t$					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
C	0.050***	0.000	-0.001	0.000	0.001	0.000
	(66.127)	(-0.044)	(-0.237)	(0.277)	(0.611)	(0.433)
$IVsk_{t-1}$	-0.046***	-0.023***	-0.024***	-0.004***	-0.004***	-0.005***
	(-41.514)	(-12.050)	(-12.094)	(-5.915)	(-5.667)	(-5.730)
$IVsp_{t-1}$		0.037***	0.037***	0.004***	0.005***	0.005***
		(19.043)	(18.924)	(6.859)	(6.412)	(6.208)
PC_{t-1}			0.002**	0.001**	0.001*	0.001
			(2.006)	(2.138)	(1.731)	(1.583)
$VIXRET_{t-1}$				0.300***	0.279***	0.275***
				(19.640)	(16.865)	(15.800)
$VIXRET_{t-2}$				0.229***	0.228***	0.235***
				(16.640)	(15.556)	(14.813)
$VIXRET_{t-3}$				0.191***	0.199***	0.193***
				(13.336)	(13.070)	(12.820)
$VIXRET_{t-4}$				0.178***	0.187***	0.188***
				(12.985)	(11.796)	(11.465)
ΔFTV_{t-1}					0.000*	0.000
					(-1.710)	(-1.452)
ΔFTV_{t-2}					0.000***	0.000***
					(-3.557)	(-3.732)
ΔFTV_{t-3}					0.000	0.000
					(-0.901)	(-1.241)
ΔFTV_{t-4}					0.000	0.000
					(1.504)	(1.123)
$FILLIQ_{t-1}$						0.000
						(-0.374)
$FILLIQ_{t-2}$						0.000
						(0.646)
$FILLIQ_{t-3}$						0.000
						(0.894)
$FILLIQ_{t-4}$						0.000**
						(2.500)
R^2	0.124	0.163	0.166	0.723	0.703	0.707
N	25,216	24,523	23,746	18,614	15,485	14,693

This table presents the influence of implied volatility skew, implied volatility spread, and the put-call ratio on VIX futures returns. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Informed trading activities in the VIX options market across varying economic policy uncertainty levels.

Dep.	$VIXRET_t$							
	$\geq P_{90}$	$\leq P_{10}$	$\geq P_{80}$	$\leq P_{20}$	$\geq P_{75}$	$\leq P_{25}$	≥ 67	$\leq P_{33}$
EPU	High	Low	High	Low	High	Low	High	Low
C	0.010*	0.001	0.012***	0.001	0.012***	-0.000	0.008***	-0.000
	(1.858)	(0.482)	(3.181)	(0.567)	(3.524)	(-0.154)	(2.640)	(-0.078)
$IVsk_{t-1}$	-0.008**	-0.002	-0.011***	-0.002**	-0.010***	-0.002*	-0.008***	-0.002**
	(-2.444)	(-1.509)	(-3.864)	(-2.093)	(-4.173)	(-1.660)	(-3.740)	(-2.176)
$IVsp_{t-1}$	-0.001	0.002	0.000	0.001	-0.001	0.002*	0.001	0.002**
	(-0.270)	(1.022)	(0.035)	(0.683)	(-0.437)	(1.896)	(0.622)	(2.248)
PC_{t-1}	-0.002	-0.003	-0.003	-0.000	-0.001	0.000	-0.000	0.001
	(-0.595)	(-1.524)	(-1.538)	(-0.141)	(-0.742)	(0.298)	(-0.263)	(0.567)
$VIXRET_{t-1}$	0.223***	0.279***	0.252***	0.256***	0.238***	0.235***	0.253***	0.263***
	(4.295)	(5.319)	(6.385)	(5.092)	(7.097)	(5.969)	(8.528)	(8.041)
$VIXRET_{t-2}$	0.216***	0.277***	0.212***	0.266***	0.235***	0.276***	0.229***	0.248***
	(5.050)	(6.106)	(5.818)	(6.176)	(7.234)	(7.450)	(7.809)	(8.268)
$VIXRET_{t-3}$	0.261***	0.226***	0.191***	0.270***	0.186***	0.268***	0.183***	0.278***
	(4.720)	(4.127)	(4.851)	(5.369)	(5.584)	(6.675)	(6.135)	(8.608)
$VIXRET_{t-4}$	0.202***	0.161***	0.215***	0.158***	0.215***	0.167***	0.221***	0.151***
	(4.299)	(3.016)	(5.198)	(3.513)	(5.886)	(4.533)	(6.804)	(5.232)
ΔFTV_{t-1}	0.000	-0.000	0.000	-0.000**	0.000	-0.000**	0.000	-0.000**
	(0.360)	(-1.367)	(0.516)	(-2.551)	(0.551)	(-2.453)	(0.323)	(-2.206)
ΔFTV_{t-2}	-0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***
	(-0.389)	(-2.839)	(0.948)	(-4.123)	(0.502)	(-4.165)	(0.501)	(-4.187)
ΔFTV_{t-3}	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***
	(0.897)	(-2.637)	(0.807)	(-3.326)	(0.877)	(-3.035)	(0.553)	(-2.938)
ΔFTV_{t-4}	0.000	-0.000**	0.000	-0.000**	0.000	-0.000**	0.000	-0.000*
	(1.140)	(-2.120)	(1.137)	(-2.331)	(1.002)	(-2.185)	(0.715)	(-1.693)

Table 5 (cont'd.)

$FILLIQ_{t-1}$	-0.000**	0.000	-0.000**	0.000	-0.000***	0.000	-0.000***	0.000
	(-2.498)	(0.296)	(-2.571)	(0.941)	(-2.737)	(1.380)	(-2.703)	(1.467)
$FILLIQ_{t-2}$	-0.000	-0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(-0.148)	(-0.328)	(-0.505)	(0.776)	(-0.298)	(1.163)	(-0.272)	(1.317)
$FILLIQ_{t-3}$	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.211)	(-0.001)	(0.669)	(0.633)	(0.593)	(0.684)	(0.578)	(1.202)
$FILLIQ_{t-4}$	-0.000*	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.835)	(0.303)	(-0.887)	(-0.780)	(-0.791)	(-0.867)	(-0.645)	(-0.825)
R^2	0.637	0.797	0.632	0.812	0.629	0.800	0.659	0.796
N	1,728	1,325	3,371	2,666	4,186	3,380	5,353	4,576

This table reports the impacts of IV skew, IV spread, and the put-call ratio on VIX futures returns under different economic policy uncertainty (EPU) levels. EPU is developed by Baker et al. (2016) to quantify policy-related economic uncertainty. Our analysis categorizes the dataset into periods of high and low EPU, specifically delineating high EPU periods at the 90%, 80%, 75%, and 67% thresholds and low EPU periods at the 10%, 20%, 25%, and 33% thresholds. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Informed trading activities in the VIX options market across varying market volatility levels.

Dep.	$VIXRET_t$							
	$\geq P_{90}$	$\leq P_{10}$	$\geq P_{80}$	$\leq P_{20}$	$\geq P_{75}$	$\leq P_{25}$	≥ 67	$\leq P_{33}$
Volatility	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*
C	0.018	0.000	0.026***	-0.001	0.019***	-0.001	0.011***	-0.000
	(1.329)	(0.172)	(4.179)	(-1.323)	(3.744)	(-1.323)	(2.988)	(-0.586)
$IVsk_{t-1}$	-0.030***	0.001	-0.023***	0.000	-0.020***	0.000	-0.016***	-0.000
	(-3.699)	(0.924)	(-5.037)	(0.481)	(-5.148)	(0.481)	(-5.554)	(-0.401)
$IVsp_{t-1}$	0.017*	-0.000	0.003	0.000	0.006*	0.000	0.007***	0.000
	(1.887)	(-0.474)	(0.720)	(1.062)	(1.770)	(1.062)	(2.769)	(0.587)
PC_{t-1}	-0.007	-0.000	-0.005	0.000	-0.003	0.000	-0.002	0.000
	(-1.035)	(-0.298)	(-1.385)	(0.341)	(-1.201)	(0.341)	(-1.095)	(0.737)
$VIXRET_{t-1}$	0.178***	0.320***	0.217***	0.300***	0.221***	0.300***	0.232***	0.284***
	(5.033)	(7.633)	(8.529)	(12.661)	(9.433)	(12.661)	(10.848)	(15.161)
$VIXRET_{t-2}$	0.124***	0.233***	0.153***	0.245***	0.158***	0.245***	0.175***	0.257***
	(3.625)	(5.146)	(6.239)	(10.215)	(6.987)	(10.215)	(8.537)	(13.374)
$VIXRET_{t-3}$	0.120***	0.236***	0.157***	0.238***	0.167***	0.238***	0.184***	0.231***
	(3.525)	(5.487)	(6.335)	(10.427)	(7.272)	(10.427)	(8.719)	(12.286)
$VIXRET_{t-4}$	0.171***	0.209***	0.202***	0.221***	0.201***	0.221***	0.209***	0.226***
	(4.776)	(5.129)	(7.545)	(9.560)	(8.116)	(9.560)	(9.323)	(12.155)
ΔFTV_{t-1}	0.000	0.000	0.000*	0.000	0.000	0.000	0.000	-0.000
	(0.979)	(0.217)	(1.748)	(0.711)	(1.636)	(0.711)	(1.408)	(-0.454)
ΔFTV_{t-2}	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000**
	(0.092)	(0.059)	(-0.134)	(-0.810)	(-0.295)	(-0.810)	(-0.607)	(-2.413)
ΔFTV_{t-3}	0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000*
	(0.043)	(-0.884)	(-0.168)	(-0.590)	(0.051)	(-0.590)	(-0.657)	(-1.736)
ΔFTV_{t-4}	0.000	-0.000	0.000*	-0.000	0.000	-0.000	0.000	-0.000
	(1.161)	(-0.958)	(1.756)	(-0.784)	(1.491)	(-0.784)	(0.902)	(-0.967)

Table 6 (cont'd.)

$FILLIQ_{t-1}$	-0.000**	-0.000	-0.000**	-0.000	-0.000**	-0.000	-0.000*	-0.000
	(-2.167)	(-0.026)	(-2.122)	(-0.270)	(-2.034)	(-0.270)	(-1.741)	(-0.639)
$FILLIQ_{t-2}$	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000
	(-0.358)	(-1.103)	(-0.324)	(0.468)	(-0.108)	(0.468)	(0.034)	(-0.198)
$FILLIQ_{t-3}$	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	-0.000
	(0.152)	(-0.247)	(0.086)	(0.325)	(0.097)	(0.325)	(0.299)	(-0.342)
$FILLIQ_{t-4}$	0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000**
	(0.379)	(0.680)	(-0.028)	(1.211)	(-0.072)	(1.211)	(0.085)	(2.047)
R^2	0.345	0.985	0.434	0.981	0.473	0.978	0.580	0.976
N	1,218	501	2,808	1,741	3,730	1,741	5,352	2,702

This table presents the effects of implied volatility skew, implied volatility spread, and the put-call ratio on the returns of VIX futures across varying degrees of market volatility in the VIX futures market. We compute the volatility as the standard deviation of all 15-minute VIX futures returns on a given day. Then, we categorize the dataset into periods of high and low VIX futures market volatility, specifically delineating high volatility periods at the 90%, 80%, 75%, and 67% thresholds and low volatility periods at the 10%, 20%, 25%, and 33% thresholds. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Informed trading activities in the VIX options market across varying Amihud's illiquidity levels.

Dep.	$VIXRET_t$							
	$\leq P_{10}$	$\geq P_{90}$	$\leq P_{20}$	$\geq P_{80}$	$\leq P_{25}$	$\geq P_{75}$	$\leq P_{33}$	$\geq P_{67}$
FILLIQ	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
C	-0.001	0.014**	-0.001	0.013***	0.000	0.008**	0.002	0.006**
	(-0.416)	(2.173)	(-0.878)	(2.956)	(0.058)	(2.002)	(1.512)	(1.994)
$IVsk_{t-1}$	-0.001	-0.018***	-0.000	-0.017***	-0.001	-0.013***	-0.002***	-0.012***
	(-0.467)	(-3.182)	(-0.129)	(-4.183)	(-1.177)	(-3.671)	(-2.711)	(-4.430)
$IVsp_{t-1}$	0.000	0.002	0.001	0.003	0.001	0.006**	-0.000	0.006***
	(0.165)	(0.354)	(1.322)	(1.259)	(0.967)	(2.132)	(-0.196)	(2.979)
PC_{t-1}	0.002	0.001	0.001	-0.002	0.001	-0.003	0.002**	-0.002
	(1.613)	(0.230)	(0.938)	(-0.728)	(0.761)	(-1.333)	(2.052)	(-1.109)
$VIXRET_{t-1}$	0.217***	0.257***	0.298***	0.229***	0.287***	0.231***	0.272***	0.238***
	(2.808)	(5.686)	(5.571)	(7.243)	(5.733)	(8.005)	(5.018)	(9.300)
$VIXRET_{t-2}$	0.197***	0.188***	0.164***	0.195***	0.152***	0.194***	0.101**	0.194***
	(2.911)	(4.395)	(3.249)	(6.276)	(3.148)	(6.853)	(2.519)	(7.692)
$VIXRET_{t-3}$	0.316***	0.123***	0.320***	0.159***	0.246***	0.168***	0.233***	0.170***
	(2.866)	(2.802)	(4.665)	(5.456)	(4.451)	(6.033)	(4.581)	(6.845)
$VIXRET_{t-4}$	0.117*	0.181***	0.102*	0.223***	0.205***	0.233***	0.290***	0.244***
	(1.793)	(3.939)	(1.915)	(6.634)	(3.941)	(7.494)	(6.132)	(8.571)
ΔFTV_{t-1}	-0.000	-0.000	-0.000	0.000	-0.000	0.000	-0.000	-0.000
	(-0.955)	(-0.414)	(-1.315)	(0.057)	(-1.344)	(0.049)	(-1.045)	(-0.216)
ΔFTV_{t-2}	-0.000**	0.000	-0.000***	0.000	-0.000***	0.000	-0.000***	-0.000
	(-2.054)	(0.288)	(-3.436)	(0.526)	(-3.256)	(0.587)	(-3.136)	(-0.098)
ΔFTV_{t-3}	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000*	-0.000
	(-1.214)	(-0.569)	(-1.355)	(-0.937)	(-1.341)	(-0.800)	(-1.652)	(-1.067)
ΔFTV_{t-4}	0.000	-0.000	-0.000	0.000	-0.000	0.000	-0.000	-0.000
	(0.302)	(-0.368)	(-0.302)	(0.043)	(-0.370)	(0.282)	(-1.152)	(-0.270)

Table 7 (cont'd.)

$FILLIQ_{t-1}$	0.002	0.000*	-0.001	0.000	-0.000	0.000	0.000	0.000
	(1.013)	(1.776)	(-0.710)	(1.033)	(-0.282)	(1.259)	(0.384)	(1.479)
$FILLIQ_{t-2}$	0.003	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
	(0.555)	(-1.365)	(1.540)	(-1.007)	(1.284)	(-0.519)	(1.073)	(-0.565)
$FILLIQ_{t-3}$	0.002	0.000	-0.000	0.000	0.001	0.000	0.000	0.000
	(0.722)	(1.042)	(-0.293)	(0.632)	(1.416)	(0.643)	(0.028)	(0.629)
$FILLIQ_{t-4}$	0.004	0.000	0.006**	0.000	0.001	0.000	0.000	-0.000
	(0.566)	(0.755)	(2.370)	(0.160)	(0.328)	(0.194)	(0.327)	(-0.023)
R^2	0.670	0.430	0.722	0.545	0.719	0.595	0.725	0.653
N	1,171	1,608	2,432	2,968	3,116	3,812	4,239	5,150

This table delineates the effects of implied volatility skew, implied volatility spread, and the put-call ratio on the returns of VIX futures, segmented by various degrees of the Amihud (2002) illiquidity measure. The illiquidity metric is calculated as the absolute returns of VIX futures divided by the dollar trading volume of VIX futures on a specific day. Then, we categorize the dataset into periods of high and low illiquidity, specifically delineating high illiquidity periods at the 90%, 80%, 75%, and 67% thresholds and low illiquidity periods at the 10%, 20%, 25%, and 33% thresholds. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Informed trading activities in the VIX options market across varying trading volume levels.

Dep.	$VIXRET_t$							
	$\leq P_{10}$	$\geq P_{90}$	$\leq P_{20}$	$\geq P_{80}$	$\leq P_{25}$	$\geq P_{75}$	$\leq P_{33}$	$\geq P_{67}$
FTV	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*
C	0.015**	-0.001	0.014***	-0.001	0.011***	-0.001	0.011***	-0.002
	(2.424)	(-0.307)	(3.045)	(-0.80)	(2.847)	(-0.493)	(3.136)	(-1.247)
$IVsk_{t-1}$	-0.016***	-0.003**	-0.017***	-0.002***	-0.015***	-0.002*	-0.014***	-0.001
	(-2.736)	(-2.114)	(-4.089)	(-3.170)	(-4.282)	(-1.795)	(-4.441)	(-1.438)
$IVsp_{t-1}$	0.003	0.002	0.004	0.002***	0.004	0.002**	0.003	0.003***
	(0.572)	(1.139)	(1.122)	(2.660)	(1.396)	(2.419)	(1.248)	(3.150)
PC_{t-1}	-0.008**	0.004***	-0.006**	0.004***	-0.003	0.002**	-0.000	0.002***
	(-2.317)	(3.946)	(-2.356)	(4.580)	(-1.050)	(2.379)	(-0.025)	(2.650)
$VIXRET_{t-1}$	-0.160	0.315***	0.049	0.344***	0.094*	0.328***	0.181***	0.305***
	(-1.643)	(7.119)	(0.771)	(21.310)	(1.869)	(10.889)	(4.313)	(11.679)
$VIXRET_{t-2}$	0.012	0.259***	0.097	0.229***	0.102**	0.236***	0.144***	0.253***
	(0.121)	(6.892)	(1.624)	(14.330)	(2.171)	(8.392)	(3.883)	(10.457)
$VIXRET_{t-3}$	0.046	0.213***	0.174***	0.178***	0.218***	0.205***	0.161***	0.220***
	(0.397)	(5.559)	(2.844)	(11.010)	(4.289)	(6.995)	(3.969)	(8.929)
$VIXRET_{t-4}$	0.066	0.160***	0.127**	0.202***	0.122***	0.182***	0.165***	0.172***
	(0.609)	(4.455)	(2.179)	(12.470)	(2.615)	(6.701)	(4.300)	(7.419)
ΔFTV_{t-1}	-0.000	-0.000*	0.000	-0.000**	0.000	-0.000*	0.000	-0.000*
	(-0.109)	(-1.712)	(1.618)	(-2.48)	(1.393)	(-1.794)	(1.179)	(-1.722)
ΔFTV_{t-2}	-0.000	-0.000***	-0.000	-0.000***	0.000	-0.000***	0.000	-0.000***
	(-1.098)	(-3.214)	(-0.528)	(-3.85)	(0.135)	(-3.999)	(0.636)	(-4.315)
ΔFTV_{t-3}	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000*	0.000	-0.000**
	(-0.859)	(-1.633)	(-2.242)	(-2.04)	(-0.802)	(-1.843)	(0.232)	(-2.026)
ΔFTV_{t-4}	-0.000	-0.000**	-0.000	-0.000	0.000	-0.000	0.000	-0.000
	(-0.721)	(-1.998)	(-0.421)	(-0.97)	(0.465)	(-0.983)	(0.817)	(-1.003)

Table 8 (cont'd.)

$FILLIQ_{t-1}$	-0.000**	-0.001**	-0.000	-0.004**	-0.000	-0.001	-0.000*	-0.001
	(-2.523)	(-1.966)	(-1.463)	(-2.090)	(-1.525)	(-1.365)	(-1.760)	(-0.829)
$FILLIQ_{t-2}$	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.502)	(-0.260)	(0.615)	(0.750)	(0.479)	(0.196)	(0.284)	(0.277)
$FILLIQ_{t-3}$	-0.000	0.000	-0.000	0.001	0.000	0.002	0.000	0.001
	(-0.003)	(0.017)	(-0.378)	(1.23)	(0.101)	(1.428)	(0.139)	(0.655)
$FILLIQ_{t-4}$	-0.000	0.003**	0.000	0.001	0.000	0.000	0.000	0.000
	(-1.586)	(1.972)	(0.174)	(1.520)	(0.182)	(0.224)	(0.159)	(0.274)
R^2	0.129	0.888	0.212	0.882	0.236	0.862	0.313	0.858
N	706	1,664	1,611	3,513	2,108	4,405	3,107	5,813

This table reports the impacts of IV skew, IV spread, and the put-call ratio on the returns of VIX futures under different levels of the trading volume. We categorize the dataset into periods of high and low VIX futures trading volume, specifically delineating high trading volume periods at the 90%, 80%, 75%, and 67% thresholds and low trading volume periods at the 10%, 20%, 25%, and 33% thresholds. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Informed trading activities in the VIX options surrounding macroeconomic announcements.

Dep.	$VIXRET_t$			
EVENT	*CPI*	*GDP*	*FOMC*	*All_ann*
C	0.003*	-0.002	0.001	0.004*
	(1.954)	(-0.404)	(0.241)	(1.749)
$IVsk_{t-1}$	-0.002**	-0.004	-0.004**	-0.008***
	(-2.260)	(-1.073)	(-2.508)	(-3.915)
$IVsp_{t-1}$	-0.001	0.008**	0.003**	0.005**
	(-0.811)	(2.146)	(2.056)	(2.571)
PC_{t-1}	-0.000	0.296***	0.001	0.001
	(-0.343)	(4.722)	(0.490)	(0.658)
$VIXRET_{t-1}$	0.338***	0.115**	0.250***	0.233***
	(6.394)	(2.008)	(4.974)	(6.315)
$VIXRET_{t-2}$	0.182***	0.223***	0.137***	0.134***
	(3.833)	(4.130)	(2.957)	(4.015)
$VIXRET_{t-3}$	0.177***	0.271***	0.231***	0.220***
	(3.732)	(4.713)	(4.534)	(6.055)
$VIXRET_{t-4}$	0.222***	0.000	0.302***	0.255***
	(4.268)	(0.821)	(5.750)	(7.180)
ΔFTV_{t-1}	0.000	-0.000	-0.000	0.000**
	(0.643)	(-0.181)	(-0.708)	(2.013)
ΔFTV_{t-2}	-0.000*	0.000	-0.000	0.000
	(-1.857)	(0.324)	(-0.730)	(0.278)
ΔFTV_{t-3}	-0.000	0.000	-0.000	-0.000
	(-1.621)	(0.827)	(-1.121)	(-0.944)
ΔFTV_{t-4}	0.000	-0.000***	-0.000	0.000
	(0.436)	(-15.877)	(-0.230)	(0.117)
$FILLIQ_{t-1}$	-0.000	-0.001	-0.000	-0.000***
	(-0.048)	(-1.340)	(-0.554)	(-4.882)
$FILLIQ_{t-2}$	-0.001	0.001**	-0.000	-0.000
	(-1.337)	(2.173)	(-0.842)	(-0.432)
$FILLIQ_{t-3}$	0.000	-0.000	0.000	-0.000
	(0.039)	(-0.730)	(0.635)	(-0.262)
$FILLIQ_{t-4}$	0.000	0.002	-0.000	0.000
	(0.741)	(0.469)	(-0.390)	(0.097)
R^2	0.743	0.771	0.664	0.557
N	2,510	878	2,412	3,948

The table details the influence of implied volatility skew, implied volatility spread, and the put-call ratio on the returns of VIX futures around economic announcement dates. During the sample period from January 1, 2008, to December 31, 2015, we selected a subsample encompassing the period from 2 days before the announcement date to 2 days after it. The t-statistics, adjusted using the Newey–West (1987) correction, are presented in parentheses. Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Table 10. Informed trading activities within the VIX options market on trading days after European holidays.

Dep.	$VIXRET_t$							
	Other Regular Trading Days				*Trading days after European holidays*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C	-0.006	-0.004**	-0.003*	-0.003*	0.005	0.004**	0.005**	0.005**
	(-1.079)	(-2.588)	(-1.712)	(-1.781)	(0.707)	(2.255)	(2.355)	(2.039)
$IVsk_{t-1}$	-0.023***	-0.001*	-0.002	-0.003**	-0.033***	-0.008***	-0.008***	-0.008***
	(-6.509)	(-1.075)	(-1.716)	(-2.510)	(-6.905)	(-5.981)	(-5.537)	(-5.281)
$IVsp_{t-1}$	0.049***	0.007***	0.007***	0.007***	0.035***	0.002	0.002	0.002
	(12.562)	(6.385)	(5.837)	(5.912)	(6.466)	(1.661)	(1.127)	(1.178)
PC_{t-1}	0.001	0.001	0.001	0.000	0.004	0.002	0.002	0.001
	(0.467)	(0.727)	(0.481)	(0.426)	(1.174)	(1.141)	(0.917)	(0.671)
$VIXRET_{t-1}$		0.308***	0.292***	0.295***		0.216***	0.147***	0.152***
		(12.227)	(10.448)	(10.022)		(8.613)	(5.202)	(5.360)
$VIXRET_{t-2}$		0.196***	0.202***	0.198***		0.322***	0.327***	0.347***
		(7.307)	(6.837)	(5.987)		(11.109)	(10.799)	(12.629)
$VIXRET_{t-3}$		0.226***	0.233***	0.227***		0.200***	0.222***	0.200***
		(10.269)	(9.652)	(10.124)		(7.874)	(8.938)	(8.947)
$VIXRET_{t-4}$		0.183***	0.182***	0.190***		0.151***	0.194***	0.193***
		(7.701)	(7.477)	(7.591)		(5.430)	(6.534)	(7.322)
ΔFTV_{t-1}			0.000***	0.000***			0.000	0.000
			(-2.768)	(-2.966)			(-0.093)	(-0.171)
ΔFTV_{t-2}			0.000***	0.000***			0.000	0.000
			(-3.859)	(-4.154)			(0.555)	(0.620)
ΔFTV_{t-3}			0.000	0.000			0.000	0.000
			(-0.459)	(-1.041)			(1.007)	(1.227)
ΔFTV_{t-4}			0.000	0.000			0.000	0.000
			(0.137)	(-0.108)			(0.777)	(0.628)
$FILLIQ_{t-1}$				0.000				0.000*
				(-0.228)				(1.774)
$FILLIQ_{t-2}$				0.000				0.000
				(-0.145)				(0.973)
$FILLIQ_{t-3}$				0.000				0.000
				(1.233)				(-1.499)
$FILLIQ_{t-4}$				0.000***				0.000
				(3.288)				(-0.981)
R^2	0.174	0.749	0.733	0.741	0.177	0.696	0.685	0.695
N	6,511	5,483	4,571	4,412	3,445	2,634	2,222	2,103

This table presents the impacts of the IV skew, IV spread, and the put-call ratio on the returns of VIX futures on trading days during and after European holidays. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Robustness checks across varying time intervals.

Dep.	$VIXRET_t$											
Interval	*30-minutes*						*45-minutes*					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
C	0.045***	-0.011***	-0.012***	-0.000	-0.001	-0.002	0.042***	-0.009***	-0.010***	-0.002	-0.003	-0.003
	(28.186)	(-5.008)	(-5.302)	(-0.221)	(-0.679)	(-0.830)	(25.521)	(-3.694)	(-3.729)	(-0.789)	(-1.066)	(-1.351)
$IVsk_{t-1}$	-0.037***	-0.014***	-0.014***	-0.005***	-0.005***	-0.005***	-0.034***	-0.014***	-0.015***	-0.003**	-0.002	-0.002
	(-16.373)	(-8.575)	(-8.627)	(-3.083)	(-2.764)	(-3.030)	(-14.638)	(-7.982)	(-8.024)	(-1.998)	(-1.095)	(-1.269)
$IVsp_{t-1}$		0.041***	0.042***	0.007***	0.008***	0.008***		0.038***	0.038***	0.007***	0.008***	0.008***
		(26.236)	(26.162)	(4.955)	(5.412)	(5.432)		(20.913)	(20.896)	(4.663)	(4.217)	(4.332)
PC_{t-1}			0.003**	0.001	0.001	0.001			0.001	-0.001	0.000	-0.000
			(2.294)	(0.750)	(0.766)	(0.615)			(0.828)	(-0.338)	(0.113)	(-0.071)
$VIXRET_{t-1}$				0.219***	0.215***	0.212***				0.263***	0.270***	0.284***
				(8.609)	(7.861)	(8.450)				(8.652)	(7.398)	(8.167)
$VIXRET_{t-2}$				0.247***	0.250***	0.244***				0.194***	0.190***	0.196***
				(9.411)	(8.909)	(8.831)				(6.343)	(5.850)	(6.028)
$VIXRET_{t-3}$				0.231***	0.238***	0.244***				0.197***	0.224***	0.215***
				(8.577)	(8.355)	(8.911)				(5.912)	(6.115)	(5.972)
$VIXRET_{t-4}$				0.179***	0.191***	0.193***				0.225***	0.242***	0.230***
				(6.994)	(6.829)	(7.164)				(6.812)	(7.138)	(6.965)
ΔFTV_{t-1}					0.000	0.000					0.000	0.000
					(1.376)	(1.182)					(0.042)	(0.001)
ΔFTV_{t-2}					-0.000	-0.000					0.000	0.000
					(-0.974)	(-1.128)					(0.537)	(0.182)

Table 11 (cont'd.)

ΔFTV_{t-3}					0.000	0.000					-0.000	-0.000
					(1.205)	(1.026)					(-0.493)	(-1.048)
ΔFTV_{t-4}					0.000	0.000					0.000	0.000
					(1.638)	(1.305)					(0.814)	(0.256)
$FILLIQ_{t-1}$						-0.000						0.001*
						(-0.665)						(1.668)
$FILLIQ_{t-2}$						0.001						-0.001
						(1.294)						(-0.674)
$FILLIQ_{t-3}$						0.000						-0.000
						(1.605)						(-0.215)
$FILLIQ_{t-4}$						-0.000						0.001
						(-0.962)						(1.343)
R^2	0.082	0.149	0.149	0.149	0.149	0.149	0.083	0.145	0.145	0.145	0.145	0.145
N	13,975	13,967	13,829	7,822	6,869	6,869	10,127	10,622	10,577	5,336	4,032	4,032

This table presents the effects of implied volatility skew, implied volatility spread, and the put-call ratio on the returns of VIX futures, analyzed at 30- and 45-minute intervals throughout the sample period spanning January 1, 2008, to December 31, 2015. The t-statistics are estimated using the Newey–West (1987) correction and reported in parentheses, while ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.