AN ANALYSIS ON THE INTRADAY TRADING ACTIVITY OF VIX DERIVATIVES

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ABSTRACT

We investigate the relation between trading activity in the VIX derivative markets and changes in the VIX index under a high-frequency framework. We find a significant relation between the signed trading variables of VIX futures and the contemporaneous changes in the VIX index. In addition, the net signed trading variables of VIX futures are significant predictors of future changes in the VIX index. Our results provide support for the informational role of VIX futures and evidence that trading activity in VIX options is likely caused by temporary liquidity shocks rather than the likelihood of informed trading.

Keywords: VIX index; VIX futures; VIX options; Trading activity.

JEL Classification: G12, G14.

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1. INTRODUCTION

In a perfectly efficient market where all information is immediately incorporated into asset prices without any delay, trades should not convey any information. As a result, investors should be unable to make any inferences from such transactions. However, in the real-world financial markets, trades can have an impact on market prices when certain investors take advantage of private information to engage successfully in trading activity more rapidly than prices can be adjusted to such information. This informational advantage particularly applies to institutional investors who are commonly regarded as informed traders.[1]

This study extends the existing literature on the newly established and rapidly growing VIX (the Chicago Board Options Exchange [CBOE] volatility index) derivatives markets by exploring the trading activity in VIX derivatives and its association with the changes in the VIX.[2] Compared to the "straddle" and "strangle" strategies adopted in the S&P 500 index options market, VIX derivatives (including both VIX futures and VIX options) offer investors a direct way of trading market volatility. Hence, a good understanding of the transmission of the volatility information across VIX derivatives and the VIX index is important.

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1 Institutional trades have been a major area of research since Kraus and Stoll (1972) found that block trades can affect market efficiency. Chakravarty (2001) subsequently confirmed that medium-sized trades provide support for the stealth trading hypothesis. Saar (2001) and Chiyachantana, Jain, Jiang, and Wood (2004) provide analyses of the information content of institutional trades whereas Dasgupta, Prat, and Verardo (2011) provide a theoretical equilibrium model to confirm the association between institutional herding and both short- and long-term returns.

2 The launch of VIX futures (options) took place on the CBOE on March 26, 2004 (February 24, 2006). Since then, as a result of the increasing demand for practical market risk management, these instruments have become the most successful new product launches in the history of the CBOE.

Although it is generally believed that investors are unlikely to have private information on marketwise (stock index) returns, unlike most asset returns, which are generally proven to be a random walk, volatility is highly predictable, particularly with regard to the measure compiled from derivatives trading.[3] Therefore, investors can transfer their volatility forecasting skills into their trades in the derivatives on marketwise volatility such as VIX, which makes these investors equivalent to volatility informed on the index level. In addition, due to the lack of derivatives on the volatility of individual stocks, VIX derivatives provide an effective alternative channel to manage the risk (volatility) of stock prices, especially for investors who hold stocks that are highly correlated with the S&P 500 index or who hold a large proportion of stocks included in the S&P 500. In other words, investors can transfer their private information on the stock volatility to their trades in VIX derivatives. This is also a reason why investors can be informed of volatility in the index level.

Informed trading has a permanent impact on the market prices of the underlying assets, whereas the price impact of liquidity trading is temporary (Schlag and Stoll, 2005). Therefore, if the trading activity of VIX derivatives conveys information and affects changes in the VIX index, we should expect a persistent relation between them (information hypothesis), which can be contemporaneous and/or lead–lag depending on the efficiency of

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[3] See, for example, Christensen and Prabhala (1998), Fleming (1998), Andersen, Bollerslev, Diebold, and Ebens (2001), Blair, Poon, and Taylor (2001), Ederington and Guan (2005), Andersen, Bollerslev, Diebold, and Labys (2003), Jiang and Tian(2005), Giot and Laurent (2007), and Taylor, Yadav, and Zhang (2010).

information flow.[4] Alternatively, if trading of VIX derivatives is driven by the demand for liquidity rather than informed trading, we should expect a temporary relation between them (liquidity hypothesis).

Our empirical analysis uses tick data on VIX futures and options between January 2008 and March 2010. We measure the information by analyzing three different types of trading activity in VIX derivatives: total number of transactions, trading volume, and dollar volume. For each type of information source, we compile the signed variables from buyer- and seller-initiated trading activities using the Lee and Ready (1991) algorithm because Pan and Poteshman (2006) suggest that singed variables contain more information.

According to signs and significance of the contemporaneous and lagged coefficients given by the primitive vector autoregressive (VAR) model suggested by Hasbrouck (1991) and Easley, O'Hara, and Srinivas (1998), we find a persistent relation between the trading activity of VIX futures and changes in the VIX index, which supports the information hypothesis. However, the association for the trading activity of VIX options is temporary, which is consistent with the liquidity hypothesis. These relations are particularly significant when we use the total number of transactions as the information source, which is in line with the stealth trading hypothesis proposed by Barclay and Warner (1993).[5] In addition,

[4] We identify only relatively minor microstructure issues, such as the problems of non-synchronized trading and stale prices, essentially because both the S&P 500 index and VIX options are traded with satisfactory liquidity on the same exchange (i.e., the CBOE).

[5] Barclay and Warner's (1993) stealth trading hypothesis suggests that informed traders prefer to concentrate on medium-sized trades. As a result, informed traders with large orders tend to divide their orders into several smaller trades and thus increase the number of transactions.

the relation become weaker during the financial crisis, which is consistent with the notion of Seo and Kim (2015) that traders can disguise their information more easily during that period.

We also use a standard VAR model to run Granger causality tests between VIX futures trading, VIX options trading, and changes in the VIX. The results show clear evidence of bi-directional causality between VIX futures trading and changes in the VIX; however, we find no evidence that VIX options trading has any causal effect on changes in the VIX. These results suggest that investors use VIX options for hedging purposes in response to changes in the VIX and that the trading activity of VIX futures can predict the movement of the VIX index.

Overall, these findings indicate that informed traders tend to act on volatility information to trade in the VIX futures market rather than the VIX options market. Three interpretations of these findings are possible. First, according to Easley et al. (1998), liquidity can be an important concern for informed traders to determine where to trade, and the liquidity of VIX futures is generally better than that of VIX options.[6] Second, unlike equity returns, volatility is highly predictable. This high predictability may attract more volatility informed traders to VIX futures, especially given that, when the trading direction is correct, trading VIX futures is more profitable than trading VIX options. Third, VIX

[6] As reported by CBOE Futures Exchange, average daily volume in VIX futures was over 200,000 contracts, whereas average daily volume in VIX options was about 60,000 contracts when the volume is adjusted for the difference in the contract denominations of the futures ($1,000 times index level) and the options ($100 times index level).

futures and options require investors to trade on different types of information. Whereas VIX futures trades only contain directional information, VIX options contains both directional and volatility information of VIX, which inevitably makes the trading activity of VIX options less informative as a directional information measure.

This study enriches the empirical literature on VIX derivatives markets by comprehensively analyzing the intraday properties and dynamics of and the information dissemination mechanism across three highly related markets (VIX index, VIX futures, and VIX options).[7] Unlike those studies that focus on the market prices of VIX derivatives, our study analyzes the informational role of intraday trading activity in VIX derivatives, which is another effective measure of the impact of swift information flow.

Our empirical findings also contribute to the debate on the effect of the information content of options trading activity on price discovery of the underlying asset. Although some studies provide empirical support for the informational role of options trading,[8] Chan, Chung, and Fong (2002) find that signed volume in equity options has no apparent information content for future stock returns. Furthermore, Schlag and Stoll (2005) show that signed trading activity of index options is more likely driven by the liquidity effect rather

[7] For example, Shu and Zhang (2012) focus on the relation between daily VIX futures prices and the VIX index, and Frijns, Tourani-Rad, and Webb (2016), who conduct bi-directional Granger causality tests between these two markets, show that the effect appears to be stronger from VIX futures prices to the VIX. In addition, Tsai, Chiu, and Wang (2015) investigate the informational role of quote changes in VIX options, and Bollen, O'Neill, and Whaley (2016) examine the price relation between the VIX index and its corresponding derivatives and find that VIX futures prices lead the VIX index.
[8] The studies include Pan and Poteshman (2006), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012), Conrad, Dittmar, and Ghysels (2013), An, Ang, Bali, and Cakici (2014), and Cremers, Halling, and Weinbaum (2015).

than the information effect. We extend this line of research by exploring the impact of information content of VIX options trading on changes in the VIX index and provide evidence against the information role of intraday trading activity in VIX options.

The remainder of this paper is organized as follows. Section 2 provides a literature review and hypothesis development. Section 3 describes the data. Section 4 presents the details of the empirical methodology adopted for our empirical analysis. Section 5 discusses the empirical results, and Section 6 provides robustness analyses of these results. Finally, Section 7 provides our conclusions.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

O'Hara (2003) argues that financial markets have two important major functions: liquidity and price discovery. Some previous studies report the presence of informed traders in the derivative markets. For example, Hasbrouck (2003) finds significant price discovery in the index futures markets, and So and Tse (2004) find that Hang Seng Index futures markets, contain the most information. Fleming, Ostdiek, and Whaley (1996) report that index futures, compared to index options and the underlying cash index, have lower transaction costs to facilitate more immediacy and provide an incentive for informed traders to collect and trade market-wide information first in the index futures market. In addition to lower transaction costs, higher financial leverage helps to explain why informed investors prefer to engage initially in trading in the options markets.[9]

However, prior research into the trading behavior of informed traders in the derivative markets is both contradictory and inconclusive. For example, Chiang and Fong (2001) show index futures and options markets do not provide leading information about the index on Hong Kong's Hang Seng Index. Chan, Chung, and Fong (2002) also do not provide any confirmatory evidence of the informational role of options. Amin and Lee (1997) and Cao, Chen, and Griffin (2005) show that options trading activity is only informative immediately prior to the release of details on certain corporate events, such as earnings and takeover announcements.

Unlike asset returns, which the literature, in general, proves to be a random walk, volatility is highly predictable, particularly when using the information contained in derivatives trading data.[10] In contrast to complex volatility trading strategies in the S&P 500 index options market, VIX derivatives offer a much simpler and more direct channel for trading future movement of market volatility without the need to deal with all of the other associated risk factors that would otherwise affect the overall performance of volatility strategies.[11] In addition, because no derivatives exist for the volatility of individual stocks,

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[9] See, for example, Bhattacharya (1987), Easley et al. (1998), Chakravarty, Gulen, and Mayhew (2004), Ni, Pan, and Poteshman (2008), Cao, Yu, and Zhong (2010), Xing, Zhang, and Zhao (2010), Johnson and So (2012), Chang, Hsieh, and Lai (2013) and Chiang (2014).

[10] Blair et al. (2001) show that implied volatility from American-style S&P 100 index options provides more accurate market volatility forecasts than either low- or high-frequency historical asset prices, whereas Jiang and Tian (2005) find model-free implied volatility calculated from the S&P 500 index options performs better than Black–Scholes implied volatility and past realized volatility for future market volatility.

[11] A sharp increase in trading volume of the VIX derivatives markets shows that these new volatility products meet the needs of investors. For instance, as the CBOE reports, trading volume in VIX futures set a new

trading of VIX derivatives can be an effective alternative strategy to manage the risk of individual stocks, especially for investors who hold stocks that are highly correlated with the S&P 500 index or take a large proportion in the S&P 500 index. Therefore, although investors are unlikely to have private information on the returns of a marketwise index, they are more likely to possess volatility information and thus to trade initially in the VIX derivatives markets. If the trading activity of VIX derivatives is informative for VIX changes, we should observe a persistent relation between them. Our first hypothesis is thus summarized as follows.

Hypothesis 1: *Trading activity in VIX derivatives contains persistent information regarding the movement of the VIX index (information hypothesis).*

Certainly, liquidity traders can also drive trading activity in the derivatives markets. Derivative market makers have to provide immediacy to investors for hedging motivation, the portfolio rebalancing needs of liquidity, and so on. If larger trading activity is mainly driven by liquidity traders, it can induce temporary deviations in the fundamental value of the underlying asset. In this case, we should observe a temporary relation between the trading activity of derivatives and the changes in the underlying asset. Taking VIX call options as an example, if market makers, who provide liquidity to traders in the VIX call options market, hedge their volatility exposure in the S&P 500 index options markets (because the VIX index,

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annual record with 51.6 million contracts in 2015.

the underlying asset of VIX options, is compiled from market prices of S&P 500 index options), the trading activity in VIX options would induce a temporary linkage with VIX changes due to the hedging behavior of market makers.[12] Easley et al. (1998) and Chan et al. (2002) find some evidence of hedging for stock options on the CBOE, and Schlag and Stoll (2005) also provide supportive evidence of a hedging motivation in the trading activity of German DAX index options. Therefore, our second hypothesis is constructed as follows.

Hypothesis 2: *Trading activity in VIX derivatives induces temporary deviations in the VIX index (The liquidity hypothesis).*

3. DATA

The primary data are the intraday VIX levels and VIX futures and options tick information. The sample period runs from January 2, 2008 to March 31, 2010, providing a total of 566 trading days. Following Bartram and Bodnar (2009), we define the crisis period as September 15, 2008 to February 27, 2009.

The choice of time frequency is an implementation issue that must be taken into consideration in the framework of intraday analysis because having sufficient transactions during a time interval is extremely important. Although many prior empirical studies examining the linkage between the stock and options markets use five-minute intervals, this interval may not be appropriate for VIX options, because investors in the VIX options market

[12] More specifically, to hedge their short volatility exposure in VIX calls, market makers take long volatility positions in the S&P 500 index options markets, which results in a temporary increase in the VIX level.

do not trade as aggressively as investors in the other options markets, such as the S&P 500 index options market. We therefore use 15-minute time intervals, which is essentially a trade-off between selecting a short time interval and having sufficient transactions during the interval to ensure that the analysis is meaningful.

3.1. VIX Levels and Changes

The intraday VIX levels are obtained from CQG Data Factory. Figure 1 shows the 15-minute VIX levels for our sample period. The mean level of the VIX index for the full sample period is about 30.8. However, ignoring the recent financial crisis period, which encompasses the collapse of Lehman Brothers, the mean level of the VIX index is about 20. Following the filing for bankruptcy protection by Lehman Brothers on September 15, 2008, the VIX jumped to an all-time high of 89.53 on October 28, 2008.[13] However, by March 2009, the level had slowly declined to 40 in October 2009. The VIX index finally returned to its pre-September 15, 2008 level.

<FIGURE 1 ABOUT HERE>

Table 1 reports the summary statistics of the VIX levels and changes in the VIX. Although the mean (standard deviation) of the changes in the VIX is only −0.03% (1.18%), the

[13] The bankruptcy of Lehman Brothers on September 15, 2008 was a surprise to most investors. The VIX level was still hovering around 25 on September 11, which indicates that, following the earlier takeovers of Fannie Mae and Freddie Mac, most investors did not believe that the U.S. government was prepared to let Lehman Brothers fail. Meanwhile, some big financial institutions in the other countries also collapsed. The surprise increased investors' perception of risk, and investors started to trade options aggressively for downside protection, which drove the VIX level higher. As a result, the VIX peaked several weeks after the Lehman Brothers bankruptcy. Investors' confidence did not return until the U.S. government passed the Troubled Asset Relief Program (TARP) and the central banks of the other countries bailed out their financial systems in October.

skewness is significantly negative and kurtosis is high. However, these two effects are clearly attributable to the significant changes that occur during the financial crisis period. This high-volatility period reveals crucial information on the extreme behavior of volatility and thus is clearly important and relevant to the investigation of the two hypotheses over this period.

<TABLE 1 ABOUT HERE>

3.2. Trading Activity of VIX Derivatives

We obtain tick data on VIX futures (VIX options) from the CBOE Futures Exchange (CBOE). In addition to excluding those transactions and quotes that violate any no-arbitrage condition, we also filter out all VIX derivatives with a time-to-maturity period of less than one week or greater than one year to avoid the issue of liquidity.

We measure trading activity in three different ways: trading volume, total number of transactions, and dollar volume. For each time interval, we calculate the trading volume by summing the total number of contracts traded across all VIX futures or options. We approximate the dollar volume by multiplying the transaction price by the number of contracts traded in each VIX contract (futures or options) and then aggregate this total across all VIX contracts. We compute the total number of transactions by counting all transactions across all VIX futures or options during a time interval.

For each type of trading activity, we compile several variables from alternative aggregation ways of signed trading activities, which Pan and Poteshman (2006) show to contain even greater information.[14] Specifically, we adopt Lee and Ready's (1991) algorithm to determine whether a transaction in the VIX futures or option markets involves buyer- or seller-initiated trading, because each transaction in our data set includes a buyer and a seller who possess contrary perspectives on the changes in the VIX index.[15]

The three signed variables in the VIX futures market are *FBuy*, *FSell*, and *FNet*. *FBuy* (*FSell*) is generated by combining the trading activities of buyer-initiated futures (seller-initiated futures) and *FNet* is generated by calculating buyer-initiated volume minus seller-initiated volume in VIX futures. Similarly, we use three signed variables for VIX options, *Positive*, *Negative*, *and ONet*. *Positive* (*Negative*) is generated by combining the trading activities of buyer-initiated calls and seller-initiated puts (seller-initiated calls and buyer-initiated puts), and *ONet* is generated by calculating the difference between *Positive* and *Negative* in VIX options.[16]

Table 2 reports the 15-minute averages of the three types of trading activity in VIX futures and the averages of all call and put options for the full period and the financial crisis period.

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[14] Pan and Poteshman (2006) construct put–call ratios from option volume initiated by buyers to open new positions and show that option trading volume contains information about future stock prices, which is not case for the normal put–call ratios.

[15] The algorithm is implemented following two steps: (i) Transactions occurring below (above) the midpoint of the bid and ask prices are classified as seller- (buyer-) initiated transactions, and (ii) transactions occurring at the midpoint of the bid and ask prices are first classified using a tick test that compares the trade price to the price of the previous transaction. Namely, if the current transaction occurs at a higher (lower) price than the previous transaction, it is classified as a buyer- (seller-) initiated transaction. If, on the basis of the previous trade, the transactions are still unclassifiable, we use a zero-uptick or a zero-downtick test, depending on the direction of the last non-zero price change.

[16] We follow the approach of Easley et al. (1998) to aggregate the transactions of options across all strike prices and maturities, unless otherwise stated. The transactions of VIX futures are similarly aggregated across all maturity periods.

<TABLE 2 ABOUT HERE>

Table 2 also shows the percentages of the corresponding averages of the signed trading activities. For the full sample, call options are clearly traded much more actively than put options; indeed, more than half of all of the transactions are buyer-initiated. The results for the financial crisis period show some noticeable differences from the non-crisis period. First, transactions in both futures and call options are far less active (in terms of both the number of transactions and trading volume), and the dollar volume is higher than that during the overall sample period. We surmise that investors may have become much more conservative during the financial crisis period, turning more toward trading in in-the-money calls as a result of risk concerns.

Second, Table 2 shows that the 15-minute averages of the total number of transactions in VIX put options during the financial crisis period is higher than that during the overall sample period. Third, the difference between buyer- and seller-initiated transactions is lower during the financial crisis period; indeed, sellers initiate most of the transactions in terms of the dollar volume for call options and both the total number of transactions and trading volume for put options. These two findings jointly suggest that investors regarded volatility to be too high during the crisis period; when it eventually reverted to the long-term average level, they were more willing to stand on the bearish side of volatility.

4. EMPIRICAL METHOD

Each information source has six signed variables (*FBuy*, *FSell*, *FNet*, *Positive*, *Negative*, and *ONet*). To analyze the interrelation between the trading activity of VIX derivatives and the changes in the VIX index, we refer to the seminal work of Hasbrouck (1991) to specify a primitive VAR model as follows:

$$\begin{aligned} \Delta VIX_t &= \alpha_0 + a_1 \Delta VIX_{t-1} + \cdots + a_p \Delta VIX_{t-p} + b_0 v_t + b_1 v_{t-1} + \cdots + b_p v_{t-p} + e_{1,t}, \\ v_t &= \gamma_0 + c_1 \Delta VIX_{t-1} + \cdots + c_p \Delta VIX_{t-p} + d_1 v_{t-1} + \cdots + d_p v_{t-p} + e_{2,t}, \end{aligned} \tag{1}$$

where ΔVIX_t is the changes in the CBOE VIX index during a 15-minute interval *t*, v_t represents a measure of signed trading activity in VIX futures or options in the interval, α_0 and γ_0 are the parameters representing intercept terms, *p* is the number of lags included in the VAR, and $e_{1,t}$ and $e_{2,t}$ are disturbance terms.[17] Note that the number of lags, *p*, is determined by the Akaike and Schwarz criteria. When these criteria indicate different lag lengths, we follow Roll, Schwartz, and Subrahmanyam (2014) to choose the lesser lag length. The criteria suggest a lag length of 2. All signed volume variables are normalized by subtracting the daily mean value and dividing by the standard deviation.

We employ the orthogonalized impulse function to detect the effects of the VIX derivatives signed variables to the changes in VIX index. Assume that a 2×2 lower triangular and positive-definite matrix P exists such that $\Sigma = PP'$. Hence, the moving average (MA) represents the primitive VAR model (Model 1) as

[17] The calendar clock (actual time) is partitioned into intervals of the same length of time, with the endpoint of each interval labeled sequentially *t = 1*, *t = 2*, and so on.

$$\begin{bmatrix} \Delta VIX_t \\ v_t \end{bmatrix} = \Phi(L)P^{-1} \begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix}$$

where $\Phi(L) = \sum_{i=0}^{\infty} \Phi_i L^i$ and Φ_i is a 2×2 matrix. The elements of the matrices, Φ_i, are the orthogonal impulse response, and they denote the effects of the standardized shock, $\begin{bmatrix} e_{1,t} \\ e_{2,t} \end{bmatrix}$, on the dynamic of $\begin{bmatrix} \Delta VIX_t \\ v_t \end{bmatrix}$ at lag j. The orthogonalized impulse response function can be used to detect the persistence of the effects of VIX derivatives signed trading activity to the changes in VIX index.

As suggested by the information hypothesis, if *FBuy*, *FNet*, *Positive*, and *ONet* (*FSell* and *Negative*) contain the informational signal of an increase (decrease) in the market volatility, the relation between VIX changes and *FBuy*, *FNet*, *Positive* and *ONet* (*FSell* and *Negative*) should be positive (negative) and persistent, with the relation decaying across time (i.e., positive [negative] coefficients b_0 and b_1).

As suggested by the liquidity hypothesis, if the impact of trading activity in VIX derivatives on the VIX is the result of liquidity shocks, the impact should be temporary. For example, a larger buying volume of S&P 500 index call and put options temporarily pushes up the level of the VIX because the VIX index is compiled from a portfolio of S&P 500 index options. At the same time, market makers in the S&P 500 index options market may take a long position in VIX calls to hedge the exposure of volatility driven by S&P 500 index options trading. This liquidity effect causes a temporary relation between buyer-initiated trading of VIX options and VIX changes. Because the impact is temporary, the coefficients b_0 and b_1, for example, will have contradictory signs. Consequently, to distinguish between the information hypothesis and the liquidity hypothesis, we focus on the sign of the lagged signed trading variables.

To examine the Granger causality relations between trading activity in VIX derivatives and movements in the VIX index, we revise Model 1 to specify a standard bivariate VAR model for all possible pairs of changes in the VIX and the trading activity variables on VIX futures or options as

$$\begin{aligned} \Delta VIX_t &= \alpha_0 + a_1 \Delta VIX_{t-1} + a_2 \Delta VIX_{t-2} + \cdots + a_p \Delta VIX_{t-p} + b_1 v_{t-1} \\ &\quad + b_2 v_{t-2} + \cdots + b_p v_{t-p} + e_{1,t} \\ v_t &= \gamma_0 + c_1 \Delta VIX_{t-1} + c_2 \Delta VIX_{t-2} + \cdots + c_p \Delta VIX_{t-p} + d_1 v_{t-1} + \\ &\quad d_2 v_{t-2} + \cdots + d_p v_{t-p} + e_{2,t}. \end{aligned} \tag{2}$$

If a lead–lag relation exists for trading activity (VIX change) to VIX change (trading activity)—that is, if v (ΔVIX) Granger-causes ΔVIX (v)—then the Wald test with F-statistics should reject the null hypothesis $b_1 = b_2 = \cdots = b_p = 0$ ($c_1 = c_2 = \cdots = c_p = 0$).

5. EMPIRICAL RESULTS

We first run the primitive VAR model (Model 1) to investigate the relation between the signed trading variables of VIX derivatives and the changes in the VIX index and then analyze the relations during the financial crisis period. Finally, we run the standard VAR model (Model 2) to explore the lead–lag or causality relation between the trading activity of VIX derivatives and VIX changes.

5.1. Relation between Trading Activity of VIX Derivatives and VIX Changes

To obtain a clear understanding of the association between trading activity in VIX derivatives and movements in the VIX index, we run the primitive VAR model (Model 1) to examine whether a significant informational or temporary relation exists between trading activity in VIX derivatives and changes in the VIX index. In particular, we focus on the sign and significance of coefficients b_0 and b_1 because Internet technology has boosted the speed of information flow substantially.

Panel A of Table 3 reports the results of the primitive VAR model with the six kinds of signed variables of trading activity. The three signed variables of VIX futures (*FBuy*, *FSell*, and *FNet*) show that clear contemporaneous relations exist between the signed variables and changes in the VIX, regardless of which type of information source is adopted. The relations from the total number of transactions are the strongest, which is consistent with the argument that the total number of transactions compared to trading volume and dollar volume is likely to capture more information if informed traders with large orders divide their orders into several smaller trades. In addition, the signs of contemporaneously and one-period lagged coefficients (b_0 and b_1) across variables are consistent with the expectation of the information hypothesis. In particular, *FNet* from all information sources not only has a contemporaneous and positive relation but also a positive leading relation with VIX changes as both coefficients b_0 and b_1 are positive and significant. This finding provides strong support for the informational role of *FNet* in the VIX futures market.

<TABLE 3 ABOUT HERE>

The results of Panel A of Table 3 are both statistically significance and economically meaningful. For instance, focusing on the total number of transactions as the information source, VIX changes increase about 14.74% when *FBuy* increases 1 standard deviation on average. More specifically, a 1 standard deviation increase in *FBuy* has a simultaneous 4.6 (= sample average of the VIX index 30.87 * 14.74%) basis point increase in the VIX index on average. Similarly, a 1 standard deviation increase in *FSell* causes a simultaneous 5.68 (= 30.89 * 18.40%) basis point decrease in the VIX index on average.

Although the coefficient b_1 is statistically insignificant in most cases, all signs are the same as those of their corresponding coefficient b_0, which implies a persistent, rather than a temporary, relation between the trading activity of VIX futures and VIX changes. Therefore, these findings therefore support the information hypothesis.

Turning to the results from the signed trading variables in VIX options (including *Positive*, *Negative*, and *ONet*), the signs of the lagged coefficients (b_1) run in the opposite direction of the signs of their corresponding contemporaneous coefficients (b_0), and some of the coefficients are statistically insignificant (Table 3, Panel A). The opposite signs of regression coefficients across information sources indicate that the impact of VIX options trading on VIX changes reverses rapidly. This finding implies that these transactions in the VIX options market are likely due to temporary liquidity shocks. Therefore, contrary to those from VIX futures, evidence from VIX options support the liquidity instead of information hypothesis.

The primitive model also allows us to trace the responses of changes in VIX to a standardized shock of signed trading variables by employing the orthogonalized impulse response function. Panel B of Table 3 shows that the responses to the concurrent and lag-one coefficients of signed variables in VIX futures have the same signs whereas the measures of VIX options trading display opposite signs. In addition, when we look at the net buying variable of VIX futures measured by total number of transactions, the contemporaneous effect of *FNet* on the changes in VIX (about 55%) is highest among all the signed variables, and this effect lasts for 30 minutes. Overall, our empirical results show that the trading activity of VIX futures is likely to contain more information than that of VIX options for the determination of VIX movements.

5.2. Relations between Trading Activity of VIX Derivatives and VIX Changes during the Financial Crisis

Seo and Kim (2015) report that informed traders can more easily conceal or disguise transactions during the periods of high uncertainty. Consequently, given that the complexity of the financial crisis increases uncertainty, we examine whether the informational advantage of sign trading variables of VIX futures is relatively weak during the financial crisis.

Table 4 provides the empirical results of the primitive VAR model for the period of financial crisis. Overall, all of the significance and signs of variables of VIX futures and options are similar to those in Table 3, Panel A, for the full sample. Specifically, all contemporaneous coefficients on the signed variables in VIX futures are still significant at the 1% significance level and the signs of the contemporaneous and one-period lagged coefficients are consistent with the prediction of the information hypothesis. In addition, the results for VIX options suggest that the trading activity of VIX options is driven by temporary liquidity shocks.

<TABLE 4 ABOUT HERE>

Panel B of Table 4 reports the response of VIX changes to a standard shock of trading activity during the financial crisis. Although the relation between the trading activity of VIX futures and VIX changes becomes weaker, the contemporaneous and one-period lagged coefficients of the signed trading variables in VIX futures are still consistent with the prediction of the information hypothesis. For example, the response of the contemporaneous *FNet* measured in the total number of transactions during the financial crisis is about 36%, compared to 55% for the whole sample. This finding suggests that informed traders can, in fact, disguise their information more easily during the financial crisis.

5.3. Predictive and Granger Causality Analysis on the Trading Activity of VIX Derivatives and VIX Changes

In addition to examining the information and liquidity hypotheses, we explore the predictive ability of the signed trading activity of VIX derivatives with regard to the changes in the VIX because prior literature shows that the VIX is the best predictor of realized volatility. To study the predictive ability of the signed trading variables, we adopt the standard VAR model detailed in Equation (2) to run the Granger causality test. We choose two lags based on the least number of lag length as suggested by the Akaike and Schwarz information criteria.

Panel A of Table 5 shows that the one-period lagged coefficients (b_1) of the signed trading variables in VIX futures are significant at least at the level of 5%, whereas the two-period lagged coefficients (b_2) are insignificant regardless of which type of information sources are used. However, the one-period lagged coefficient (b_1) of the signed VIX options variables are statistically insignificant except for the net trading variable measured by the total number of transactions. The superior forecast ability of the signed VIX futures variables implies that volatility informed traders prefer to realize their information in the VIX futures market rather than in the VIX options markets, although VIX index rapidly (within 15 minutes) incorporates the information contained in the trading activity.

<TABLE 5 ABOUT HERE>

Panel B of Table 5 reports the results of the Granger causality test. Bi-directional Granger causality relations exist between signed variables of VIX futures and VIX changes, especially for the information source from the total number of transactions. In addition the signed variables of VIX options cannot reject the null hypothesis that the trading activity of VIX options does not Granger-cause VIX changes, whereas VIX changes significantly Granger-cause the three signed variables of VIX options measured by the total number of transactions. This result suggests that investors use VIX options as a hedge against changes in market volatility.

One possible reason that trading activity of VIX derivatives is caused by VIX changes is mean-reverting property of volatility, which is well-documented in the finance literature (e.g., Campbell, Lo, and MacKinlay, 1997; Fouque, Papanicolaou, and Sircar, 2000). Some investors may develop trading strategies to take advantage of this mean-reverting property. For example, when the VIX index rises above a specific level, investors may easily forecast a downward pattern, and thus they take a short position in VIX futures and VIX calls or a long position in VIX puts. Another reason may be related to hedging motivations: Investors more likely go long in VIX calls or short in VIX puts as a hedge against market volatility when the VIX continues to climb.

6. ROBUSTNESS ANALYSIS

6.1. Impacts of Intraday Trading Patterns

Because intraday data commonly displays a particular periodical pattern, we explore whether an intraday pattern exists in our data and, if so, whether it affects our empirical results. Figure 2 illustrates the intraday pattern of the total number of transactions for VIX futures and options by taking the average across sample days for each 15-minute time interval. The results show obvious intraday periodical patterns in the trading activity of VIX futures and options, with the intraday patterns of the two time series being quite similar. They are both roughly U-shaped with higher levels for those intervals close to the open and close periods.[18]

<FIGURE 2 ABOUT HERE>

Thus, to exclude the effect of the intraday periodical patterns, we rerun the primitive VAR model (Model 1) using transactions that only occur between the trading hours of 9:45 AM and 2:30 PM. Table 6 shows that the results are similar to those from the full sample. Therefore, our conclusions hold. The response of the concurrent effect of *FNet* using the total number of transactions as the information source is about 33%, which is the highest among all signed VIX derivatives variables.

<TABLE 6 ABOUT HERE>

6.2. The Issue of Sampling Frequency

[18] Figure 2 provides the results measured by the total number of transactions. Figures for the other two activity sources are available on request.

Although we provide a rationale for selecting the 15-minute frequency, we examine the impact of the sampling frequency on the association between the signed trading variables and VIX changes. We focus on the net buying variable of VIX futures (*FNet*) because it is most informative in our previous analysis. Using different frequencies including 30-minute, 45-minute, and 60-minute intervals, we rerun the primitive VAR model to determine the impact of sampling frequency on our empirical results.

Panel A of Table 7 reports the results using the alternate time intervals. All contemporaneous coefficients (b_0) are positively significant regardless of which sampling frequency is adopted. However, the *t*-statistic values of the concurrent coefficient show that the information content of trading activity in VIX futures monotonically decrease from the 15-minute to the 60-minute sampling frequency. In addition, the significance of the lag-one coefficients disappears for the longer sampling frequency, implying that the volatility information contained in VIX futures is rapidly transmitted to the VIX index. This finding is consistent with the information efficiency between VIX and VIX futures as suggested by Shu and Zhang (2012) using daily data.

<TABLE 7 ABOUT HERE>

Panel B of Table 7 reports the results of the response of the changes in VIX to a standardized shock in *FNet*. The contemporaneous and one-period lagged coefficients have the same sign at the 15-minute and 30-minute sampling frequencies regardless of which information source is adopted. Although the signs of the one-period lagged coefficients at the 45-minute and 60-minute sampling frequencies in terms of the number of transactions turns negative, both are statistically insignificant even at the 90% significance level. Overall, the evidence of the net trading variable in VIX futures on VIX changes remains consistent with the prediction of the information hypothesis.

7. CONCLUSIONS

We investigate information transmission between derivatives and the underlying asset markets by examining the intraday relationships between changes in the VIX index and trading activity in VIX futures and options. Focusing on intraday data using 15-minute time intervals, we investigate the contemporaneous and lead–lag relations between changes in the VIX and the signed VIX derivatives trading to show that the VIX futures (options) trading follows the information (liquidity) hypothesis. Our results also show that signed VIX futures (options) volume following the information (liquidity) hypothesis have predictive power (insignificant predictive power) related to changes in VIX. Overall, our empirical findings suggest that investors use VIX options for hedging purposes in response to changes in the VIX, whereas trading activity of VIX futures predicts changes in the VIX.

This research can be extended to explore the information content of trading activity of VIX derivatives across various categories of investors (e.g., individual and institutional investors) if more detailed data become available. By examining the trading behavior of various categories of investors, we can better understand which trades are more informative. If the data set contains investors' identifications, we may be able to specifically identify informed traders.

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Table 1. Descriptive statistics of 15-minute VIX levels

This table reports the summary statistics of 15-minute VIX levels and the percentage changes in the VIX for the sample period of January 2, 2008 to March 31, 2010, providing a total of 566 trading days. The table also reports the autocorrelation function with up to five lags and the augmented Dickey–Fuller (ADF) test statistics.

Variables	VIX Level	Change in the VIX (%)
Mean	30.87	–0.03
Std. Dev.	13.08	1.18
Skewness	1.49	–0.45
Kurtosis	4.63	193.81
Min.	15.97	–38.18
Max.	85.48	36.48
ACF		
Lag 1	0.99	–0.01
Lag 2	0.99	0.02
Lag 3	0.99	0.03
Lag 4	0.98	0.00
Lag 5	0.98	–0.01
Unit-root ADF test	–2.17	–123.53

Table 2. Trading activity in VIX futures and options

This table reports the 15-minute averages of the trading volume, number of transactions, and dollar volume of VIX futures as well as the VIX call and put options; these include the full sample period running from January 2, 2008 to March 31, 2010, and the crisis period (encompassing the collapse of Lehman Brothers) running from September 15, 2008 to February 27, 2009. Each transaction is classified as a buyer- or seller-initiated transaction based upon the Lee–Ready algorithm (1991). The figures in the parentheses represent the percentages of the corresponding averages of the available signed trading activities.

	Futures		Call Options		Put–Options	
Variables	Full sample	Crisis period	Full sample	Crisis period	Full sample	Crisis period
Trading Volume						
Buyer-initiated	66.67	44.75	1501.29	692.25	970.24	494.25
	(50.35)	(49.50)	(54.08)	(51.39)	(52.21)	(49.74)
Seller-initiated	65.73	45.65	1274.96	654.75	888.17	499.50
	(49.65)	(50.50)	(45.92)	(48.61)	(47.79)	(50.26)
No. of Transactions						
Buyer-initiated	24.92	18.92	16.01	15.65	7.38	9.10
	(49.81)	(49.04)	(50.52)	(51.48)	(50.17)	(47.95)
Seller-initiated	25.11	19.66	15.68	14.75	7.33	9.88
	(50.19)	(50.96)	(49.48)	(48.52)	(49.83)	(52.05)
Dollar Volume						
Buyer-initiated	1841.48	1838.52	2611.96	3730.61	1218.91	1136.50
	(50.13)	(49.24)	(51.20)	(48.04)	(53.99)	(50.57)
Seller-initiated	1831.76	1895.48	2489.05	4035.22	1037.59	1111.07
	(49.87)	(50.76)	(48.80)	(51.96)	(46.01)	(49.43)

Table 3. Relations between trading activity of VIX derivatives and VIX changes

Panel A reports the estimation results for the measures of trading activity (v_t), including the trading volume, number of transactions, and dollar volume, based on the following primitive VAR model with the two lag terms:

$$\Delta VIX_t = \alpha_0 + a_1 \Delta VIX_{t-1} + a_2 \Delta VIX_{t-2} + b_0 v_t + b_1 v_{t-1} + b_2 v_{t-2} + e_{1,t}$$

$$v_t = \gamma_0 + c_1 \Delta VIX_{t-1} + c_2 \Delta VIX_{t-2} + d_1 v_{t-1} + d_2 v_{t-2} + e_{2,t}$$

where ΔVIX_t is the change in the VIX; v_t is the trading activity measure of interest; $e_{1,t}$ and $e_{2,t}$ are both the innovation for ΔVIX_t and v_t individually; The time interval is 15 minutes, with the sample period running from January 2, 2008 to March 31, 2010. *FBuy* (*FSell*) refers to the buyer- (seller-) initiated VIX futures; *FNet* indicates the difference between *FBuy* and *FSell*; *Positive* (*Negative*) is the trading activity obtained by combining buyer-initiated calls and seller-initiated puts (seller-initiated calls and buyer-initiated puts); and *ONet* indicates the difference between *Positive* and *Negative*. *t*-statistics are reported in parentheses. Panel B presents that the orthogonalized impulse response function and shows the response of changes in the VIX to the standard shocks of these signed VIX futures or options variables. * indicates significance at the 1% levels.

Panel A. Coefficients estimation of primitive vector autoregressive model

	Trading Volume		No. of Transactions		Dollar Volume	
Trading Activity Measure	b_0	b_1	b_0	b_1	b_0	b_1
FBuy	0.1006*	0.0129	0.1474*	0.0152	0.1017*	0.0098
	(9.92)	(1.04)	(14.11)	(1.01)	(10.02)	(0.95)
FSell	–0.1344*	–0.0078	–0.1840*	–0.0126	–0.1347*	–0.0095
	(–13.33)	(–0.77)	(–13.09)	(–0.73)	(–13.37)	(–0.93)
FNet	0.2500*	0.0352*	0.3653*	0.0391*	0.2511*	0.0356*
	(26.04)	(2.50)	(39.00)	(3.79)	(26.16)	(2.55)
Positive	0.0267*	–0.0139	0.1637*	–0.0479*	0.0185	–0.0137
	(3.28)	(–1.90)	(15.97)	(–4.61)	(1.54)	(–1.38)
Negative	–0.0113	0.0047	–0.1493*	0.0298*	–0.0114	0.0122
	(–1.38)	(0.58)	(–14.43)	(2.85)	(–1.16)	(1.24)
ONet	0.0289*	–0.0112*	0.3088*	–0.0240*	0.0162	–0.0026
	(3.35)	(–2.01)	(32.22)	(–2.35)	(1.58)	(–0.26)

(*Table 3 continues*)

Table 3 (continued)

Panel B. The responses of VIX changes to order flow of VIX futures or options

Trading	Information Source																	
Activity	Trading Volume						No. of Transactions						Dollar Volume					
Measure	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
FBuy	0.1707*	0.0231	–0.0414	–0.0010	–0.0055	–0.0014	0.2129*	0.0412	–0.0159	–0.0007	–0.0055	–0.0016	0.1754*	0.0240	–0.0031	–0.0011	–0.0057	–0.0014
FSell	–0.1922*	–0.0724*	–0.0010	–0.0095	–0.0023	–0.0014	–0.2632*	–0.0582*	–0.0145	–0.0146	–0.0056	–0.0033	–0.1918*	–0.0751*	–0.0010	–0.0096	–0.0023	–0.0014
FNet	0.3744*	0.0953*	–0.0383	0.0009	0.0003	0.0001	0.5528*	0.1391*	–0.0086	–0.0005	0.0000	0.0003	0.3758*	0.0962*	–0.0373	0.0007	0.0003	0.0001
Positive	0.0517*	–0.0243	–0.0236	0.0015	–0.0004	–0.0000	0.2994*	–0.0130	–0.0399	–0.0055	–0.0057	–0.0020	0.0362	–0.0153	–0.0569*	0.0015	–0.0012	–0.0000
Negative	–0.0156	0.0163	0.0020	–0.0001	0.0000	–0.0000	–0.2045*	0.0082	–0.0253	0.0084	0.0050	0.0023	–0.0079	0.0029	0.0136	–0.0003	0.0000	–0.0000
ONet	0.0507*	–0.0429*	–0.0055	–0.0008	0.0001	0.0000	0.3209*	–0.0232	0.0223	–0.0056	–0.0026	–0.0008	0.0038	–0.0082	–0.0393	0.0030	0.0004	–0.0000

Table 4. Relation between trading activity of VIX derivatives and VIX changes in the financial crisis period

Panel A reports the estimation results for the measures of trading activity (v_t), including the trading volume, number of transactions, and dollar volume, based on the following primitive VAR model with the two lag terms:

$$\Delta VIX_t = \alpha_0 + a_1\Delta VIX_{t-1} + a_2\Delta VIX_{t-1} + b_0 v_t + b_1 v_{t-1} + b_2 v_{t-2} + e_{1,t}$$

$$v_t = \gamma_0 + c_1\Delta VIX_{t-1} + c_2\Delta VIX_{t-2} + d_1 v_{t-1} + d_2 v_{t-2} + e_{2,t}$$

where ΔVIX_t is the change in the VIX; v_t is the trading activity measure of interest; $e_{1,t}$ and $e_{2,t}$ are both the innovation for ΔVIX_t and v_t individually. The time interval is 15 minutes, with the sample period running from September 15, 2008 to February 27, 2009. *FBuy* (*FSell*) refers to the buyer- (seller-) initiated VIX futures; *FNet* indicates the difference between *FBuy* and *FSell*; *Positive* (*Negative*) is the trading activity obtained by combining buyer-initiated calls and seller-initiated puts (seller-initiated calls and buyer-initiated puts); and *ONet* indicates the difference between *Positive* and *Negative*. *t*-statistics are in parentheses. Panel B presents that the orthogonalized impulse response function and shows the response of changes in the VIX to the standard shocks of these signed VIX futures or options variables. * indicates significance at the 1% level.

Panel A. Coefficients estimation of vector autoregressive model

	Trading Volume		No. of Transactions		Dollar Volume	
Trading Activity Measure	b_0	b_1	b_0	b_1	b_0	b_1
FBuy	0.1814*	0.0086	0.2308*	0.0128	0.1865*	0.0084
	(5.16)	(0.24)	(6.45)	(0.36)	(5.30)	(0.24)
FSell	–0.2053*	–0.0467	–0.2854*	–0.0144	–0.2049*	–0.0495
	(–5.82)	(–1.31)	(–8.01)	(–0.40)	(–5.80)	(–1.39)
FNet	0.3818*	0.1163	0.5647*	0.1391*	0.3832*	0.1174
	(11.54)	(1.63)	(17.51)	(2.92)	(11.57)	(1.93)
Positive	0.0527	0.0271	0.3233*	–0.0688	0.0370	0.0164
	(1.55)	(0.80)	(9.13)	(–1.90)	(1.09)	(0.48)
Negative	–0.0160	–0.0167	–0.2225*	0.0536	–0.0080	–0.0031
	(–0.47)	(–0.49)	(–6.19)	(1.82)	(–0.24)	(–0.09)
ONet	0.0517	0.0483	0.3313*	–0.0538*	0.0039	0.0086
	(1.52)	(1.43)	(14.20)	(–2.79)	(0.12)	(0.25)

(Table 4 continues)

Table 4 (continued)

Panel B. The responses of VIX changes to order flow of VIX futures or options

Trading Activity Measure	Information Source																	
	Trading Volume						No. of Transactions						Dollar Volume					
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
FBuy	0.0952*	0.0081	–0.0058	–0.0007	–0.0010	–0.0003	0.1349*	0.0256	–0.0181	–0.0026	–0.0037	–0.0014	0.0962*	0.0074	–0.0075	–0.0012	–0.0013	–0.0004
FSell	–0.1275*	–0.0355	0.0017	–0.0024	–0.0001	–0.0000	–0.1684*	–0.0287	–0.0110	–0.0060	–0.0027	–0.0015	–0.1279*	–0.0371	0.0003	–0.0029	–0.0003	–0.0003
FNet	0.2451*	0.0637*	–0.0023	0.0004	–0.0001	0.0000	0.3573*	0.0898*	0.0002	0.0001	–0.0001	0.0000	0.2461*	0.0641*	–0.0022	0.0004	–0.0001	0.0000
Positive	0.0261	–0.0097	0.0024	0.0005	0.0000	0.0000	0.1524*	–0.0034	–0.0236	–0.0077	–0.0050	–0.0020	0.0181	–0.0118	–0.0131	–0.0014	–0.0003	–0.0000
Negative	–0.0110	0.0093	–0.0024	0.0016	0.0002	0.0000	–0.1379*	0.0138	–0.0151	–0.0051	–0.0027	–0.0012	–0.0111	0.0129	–0.0039	–0.0006	–0.0001	–0.0000
ONet	0.0285	–0.0101	0.0036	–0.0007	–0.0002	–0.0000	0.2999*	–0.0100	–0.0221	–0.0030	–0.0007	0.0000	0.0159	–0.0021	–0.0062	–0.0002	0.0000	0.0000

Table 5. Predictive and Granger causality analysis on trading activity in VIX derivatives

$$\Delta VIX_t = \alpha_0 + a_1 \Delta VIX_{t-1} + a_2 \Delta VIX_{t-2} + b_1 v_{t-1} + b_2 v_{t-2} + e_{1,t}$$

$$v_t = \gamma_0 + c_1 \Delta VIX_{t-1} + c_2 \Delta VIX_{t-2} + d_1 v_{t-1} + d_2 v_{t-2} + e_{2,t}$$

Panel A reports the estimation results for the measures of trading activity (v_t), including the trading volume, number of transactions, and dollar volume, based on the abovementioned standard VAR model (2). *t*-statistics are reported in parentheses. Panel B presents the results of Granger-causality test between these six signed variables and the VIX changes across three trading measures. * indicates significance at the 1% level.

Panel A. Estimation of vector autoregressive model

Trading Activity	Trading Volume		No. of Transactions		Dollar Volume	
Measure	b_1	b_2	b_1	b_2	b_1	b_2
FBuy	0.0206	–0.0101	0.0332*	–0.0163	0.0197	–0.0118
	(2.01)	(–0.99)	(3.14)	(–1.54)	(1.98)	(–1.16)
FSell	–0.0384*	0.0128	–0.0329*	0.0013	–0.0402*	0.0117
	(–3.78)	(1.26)	(–3.11)	(0.12)	(–3.95)	(1.15)
FNet	0.0477*	–0.0092	0.0690*	–0.0116	0.0482*	–0.0091
	(4.76)	(–0.92)	(6.70)	(–1.12)	(4.80)	(–0.91)
Positive	–0.0051	–0.0051	–0.0029	–0.0282*	–0.0120	–0.0127
	(–0.52)	(–0.52)	(–0.28)	(–2.72)	(–1.22)	(–1.29)
Negative	–0.0012	–0.0031	–0.0159	–0.0089	–0.0133	–0.0026
	(–0.12)	(–0.32)	(–1.52)	(–0.85)	(–1.35)	(–0.27)
ONet	–0.0027	–0.0033	0.0219*	–0.0307*	–0.0021	–0.0066
	(–0.27)	(–0.34)	(2.14)	(–3.02)	(–0.21)	(–0.67)

Panel B. Granger causality tests

	H_0: VIX changes does not Granger-cause trading activity changes						H_0: Trading activity changes does not Granger-cause VIX changes					
	FBuy	*FSell*	*FNet*	*Positive*	*Negative*	*ONet*	*FBuy*	*FSell*	*FNet*	*Positive*	*Negative*	*ONet*
Trading Volume	4.96*	8.03*	1.36	0.74	0.78	2.09	0.71	7.19*	11.56*	0.29	0.06	0.10
No. of Transactions	12.8*	28.96*	5.45*	5.83*	3.90*	72.94*	6.20*	5.38*	22.65*	4.36	2.17	4.57
Dollar Volume	4.20	9.41*	1.45	0.90	0.05	0.45	0.83	7.83*	11.79*	1.74	0.98	0.24

Table 6. Relation between trading activity of VIX derivatives and VIX changes with controlling for the intraday patterns

Panel A reports the estimation results for the measures of trading activity (v_t), including the trading volume, number of transactions, and dollar volume, based on the following primitive VAR model with the two lag terms:

$$\Delta VIX_t = \alpha_0 + a_1 \Delta VIX_{t-1} + a_2 \Delta VIX_{t-2} + b_0 v_t + b_1 v_{t-1} + b_2 v_{t-2} + e_{1,t}$$

$$v_t = \gamma_0 + c_1 \Delta VIX_{t-1} + c_2 \Delta VIX_{t-2} + d_1 v_{t-1} + d_2 v_{t-2} + e_{2,t}$$

where ΔVIX_t is the change in the VIX; v_t is the trading activity measure of interest; $e_{1,t}$ and $e_{2,t}$ are both the innovation for ΔVIX_t and v_t individually. The time interval is 15 minutes, with the sample period running from January 2, 2008 to March 31, 2010 and it starts at 9:45 AM and ends at 2:30 PM in each trading day. *FBuy* (*FSell*) refers to the buyer- (seller-) initiated VIX futures; *FNet* indicates the difference between *FBuy* and *FSell*; *Positive* (*Negative*) is the trading activity obtained by combining buyer-initiated calls and seller-initiated puts (seller-initiated calls and buyer-initiated puts); and *ONet* indicates the difference between *Positive* and *Negative*. *t*-statistics are in parentheses. Panel B presents that the orthogonalized impulse response function and shows the response of changes in the VIX to the standard shocks of these signed VIX futures or options variables. * indicates significance at the 1% level.

Panel A. Coefficients estimation of vector autoregressive model

	Trading Volume		No. of Transactions		Dollar Volume	
Trading Activity Measure	b_0	b_1	b_0	b_1	b_0	b_1
FBuy	0.1648*	0.0084	0.2102*	0.0097	0.1648*	0.0086
	(13.01)	(0.65)	(17.51)	(0.79)	(13.19)	(0.67)
FSell	–0.1754*	–0.0002	–0.1914*	–0.0016	–0.1756*	–0.0003
	(–14.07)	(–0.01)	(–15.83)	(–0.13)	(14.08)	(–0.02)
FNet	0.2856*	0.0303*	0.3856*	0.0398*	0.2873*	0.0325*
	(26.08)	(2.60)	(37.70)	(3.43)	(26.23)	(2.78)
Positive	0.0357*	–0.0186*	0.1722*	–0.0201*	0.0278*	–0.0174*
	(4.16)	(–2.16)	(15.65)	(–1.91)	(3.23)	(–2.02)
Negative	0.0017	–0.0043	–0.1235*	0.0184*	–0.0052	0.0098
	(0.16)	(–0.42)	(–10.97)	(1.82)	(–0.51)	(0.96)
ONet	0.0290*	–0.0117	0.2722*	–0.0182*	0.0087	0.0038
	(3.41)	(–1.87)	(26.53)	(–1.93)	(0.84)	(0.37)

(Table 6 continues)

Table 6. (continued)

Panel B. The responses of VIX changes to a standardized shock of innovations of signed VIX derivatives variables																		
Trading Activity Measure	Information Source																	
	Trading Volume						No. of Transactions						Dollar Volume					
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
FBuy	0.1202*	0.0194	–0.0029	0.0010	–0.0007	0.0000	0.1608*	0.0152	0.0020	0.0004	–0.0002	–0.0000	0.1219*	0.0198	–0.0043	0.0009	–0.0009	–0.0000
FSell	–0.1298*	–0.0142	0.0063	0.0001	0.0011	0.0001	–0.1457*	–0.0219	–0.0099	–0.0024	–0.0009	–0.0002	–0.1299*	–0.0144	0.0058	0.0001	0.0010	0.0001
FNet	0.2354*	0.0842	–0.0042	0.0009	–0.0004	0.0001	0.3294*	0.1147*	0.0126	0.0004	0.0007	–0.0000	0.2366*	0.0858*	–0.0050	0.0010	–0.0005	0.0001
Positive	0.0325	–0.0114	0.0016	0.0002	0.0001	0.0000	0.1441*	–0.0045	–0.0035	–0.0019	–0.0010	–0.0003	0.0253	–0.0115	0.0040	0.0007	0.0001	0.0000
Negative	0.0015	–0.0039	0.0078	0.0000	0.0005	–0.0000	–0.1016*	0.0011	–0.0017	–0.0007	–0.0009	–0.0001	–0.0048	0.0088	–0.0082	0.0003	–0.0005	0.0001
ONet	0.0266	–0.0073	–0.0021	–0.0002	–0.0001	–0.0000	0.2390*	–0.0046	0.0015	–0.0019	–0.0002	–0.0001	0.0079	0.0034	–0.0013	0.0001	–0.0001	0.0000

Table 7. Relation between trading activity of VIX derivatives and VIX changes at different sampling frequencies

Panel A reports the estimation results for the measures of trading activity (v_t), including the trading volume, number of transactions, and dollar volume, based on the abovementioned primitive VAR model (1) with the two lag terms. The time intervals are 15 minutes, 30 minutes, 45 minutes, and 60 minutes, with the sample period running January 2, 2008 to March 31, 2010. We only present the results of the signed variable, *FNet*. *t*-statistics are in parentheses. Panel B presents that the orthogonalized impulse response function and shows the response of changes in the VIX to the standard shocks of these signed VIX futures or options variables. * indicates significance at the 1% level.

Panel A. Coefficients estimation of vector autoregressive model

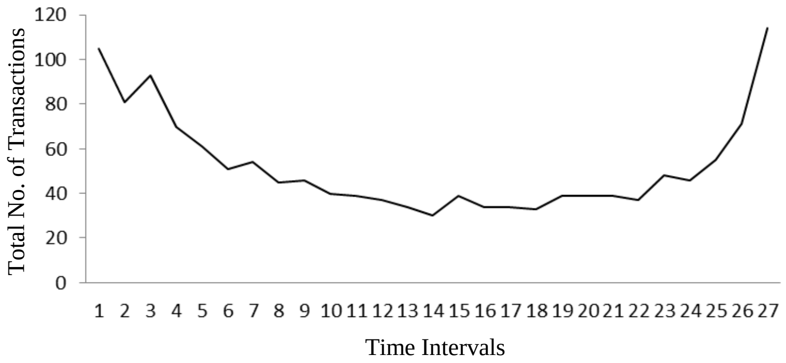
	Information Source					
	Trading Volume		No. of Transactions		Dollar Volume	
FNet	b_0	b_1	b_0	b_1	b_0	b_1
15-min interval	0.2500*	0.0352*	0.3653*	0.0391*	0.2511*	0.0356*
	(26.04)	(2.50)	(39.00)	(3.79)	(26.16)	(2.55)
30-min interval	0.4303*	0.0289	0.5711*	0.0067	0.4311*	0.0304
	(22.35)	(1.41)	(30.48)	(0.32)	(22.40)	(1.48)
45-min interval	0.4999*	0.0047	0.7017*	-0.0063	0.5006*	0.0060
	(16.82)	(0.15)	(24.26)	(-0.20)	(16.85)	(0.19)
60-min interval	0.6274*	0.0009	0.7992*	-0.0581	0.6258*	0.0024
	(14.00)	(0.02)	(18.30)	(-1.22)	(13.96)	(0.05)

Panel B. The responses of VIX changes to a standardized shock of innovations of FNet

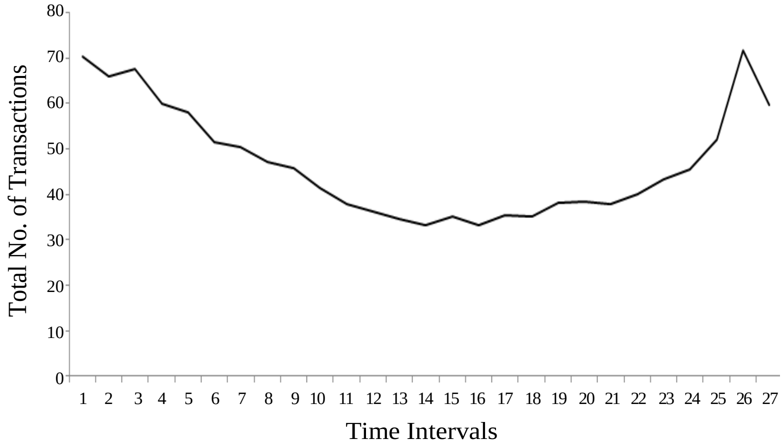
	Information Source																	
	Trading Volume						No. of Transactions						Dollar Volume					
FNet	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
15-min interval	0.3744*	0.0953*	–0.0383	0.0009	0.0003	0.0001	0.5528*	0.1391*	–0.0086	–0.0005	0.0000	0.0003	0.3758*	0.0962*	–0.0373	0.0007	0.0003	0.0001
30-min interval	0.4127*	0.0536*	–0.0366	–0.0034	0.0022	0.0002	0.5478*	0.0482	–0.0444	–0.0030	0.0022	0.0002	0.4134*	0.0554*	–0.0361	–0.0035	0.0022	0.0002
45-min interval	0.4686*	0.0016	–0.0703	0.0032	0.0062	–0.0007	0.6572*	–0.0105	–0.0684*	0.0050	0.0067	–0.0009	0.4693*	0.0004	–0.0721*	0.0029	0.0064	–0.0006
60-min interval	0.5607*	0.0796*	–0.0646	0.0228	0.0061	–0.0045	0.7179*	–0.0283	–0.0883	0.0287	0.0070	–0.0047	0.5591*	0.0781*	–0.0662	0.0229	0.0064	–0.0046

Figure 1: 15-minute VIX index levels

This figure illustrates the time series of the 15-minute VIX level, with the sample period running from January 2, 2008 to March 31, 2010.



Panel A. VIX futures



Panel B. VIX options

Figure 2. Intraday trading activity patterns in VIX futures and options

Panel A (Panel B) illustrates the intraday patterns of the total number of transactions for VIX futures (options). The trading hours for both instruments in the CBOE start at 8:30 AM and end at 3:15 PM. We take the average across 15-minute time intervals each trading day; thus, each day has a total of 27 intervals. The sample period runs from January 2, 2008 to March 31, 2010.